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Abstract

News containing important financial and economic information plays a crucial role in the process of investment and trading in financial markets. Sudden large changes and strong fluctuations observed in asset prices are normally related to the arrival of certain important news. However, the relationship between market reaction and news flow is complex and ambiguous. This thesis focuses on two classes of important news—firm-specific and macroeconomic announcements—and the impact of firm-specific announcements and macroeconomic announcements on jumps and variance of stock prices. Jumps, as abnormally large returns, and variance, measuring market fluctuations, are the two most important financial risk variables. A clear investigation into the impact of these two classes of news on jumps and variance will substantially contribute to financial risk management.

The first part of this thesis concentrates on the impact of news on jumps. First, a non-parametric statistical framework is introduced to examine the association between news arrivals and jumps in stock prices. To uncover the market reaction to news alerts, I focus on the time distances (waiting time) between news arrivals and the nearest detected jumps. For a given news item, both backward and forward waiting times are calculated with the jumps detected before and after the news arrival. In particular, backward waiting times may reflect possible information leakage. To examine whether observed jumps are associated with real news, a set of timestamps of general reference news is simulated considering intraday seasonality. Applying non-parametric tests, we are able to extract the statistical profiles of the empirical waiting times and their simulated references. As a result, the association between news and jumps is quantitatively demonstrated.

Taking advantage of the developed statistical framework, a thorough empirical analysis is implemented using Nordic and U.S. data to show the impacts of Nordic firm-specific and U.S. macroeconomic announcements on stock prices in both Nordic and U.S. markets. Specifically, the impact of scheduled and non-scheduled firm-specific announcements on Nordic stock prices is tested. I also investigate the sizes of jumps related to Nordic scheduled and non-scheduled firm-specific announcements following the same non-parametric methodology. In order to feature the importance of certain types of firm-level news, such as acquisitions, five important firm-specific announcements are selected to test their impact on Nordic stock prices in term of jumps. Regarding U.S. economic news, I provide empirical results for the impact of U.S. macroeconomic announcements on the U.S. stock index. In addition, U.S. macroeconomic announcements are grouped by announcing time. Their impacts on Nordic stock prices are studied to examine the importance of announcing clock time and the global influence of U.S. economic releases.

The second part in this research relates to the impact of macroeconomic news on equity variance modeling and the related option valuation performance with GARCH models. Impact variables of macroeconomic news are constructed using both the arrival timings

of U.S. macroeconomic announcements and realized variance, and are incorporated into classical GARCH models. The impact variables of macroeconomic news slightly improve the joint likelihood of returns and VIX for all models compared with standard GARCH models. Regarding option valuation, an affine GARCH model with news event data consistently outperforms a pure affine GARCH model. However, there is no such consistent result for NGARCH and GJR models, implying that the explicit use of macroeconomic news events data does not improve the performance of variance modeling and option pricing with non-affine GARCH models.

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Contents

Acronyms and Symbols

AR(1)	Autoregressive Process of First Order
CDF	Cumulative Distribution Function
DTM	Days to Maturity
FOMC	Federal Open Market Committee
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
GJR	Glosten-Jagannathan-Runkle
H-N	Heston-Nandi
K-S	Kolmogorov-Smirnov test
IID	Independently and Identically Distributed
MLE	Maximum Likelihood Estimation
NGARCH	Nonlinear GARCH
QMLE	Quasi Maximum Likelihood Estimation
RMSE	Root-Mean-Square-Error
*	Significance Level: 0.05
**	Significance Level: 0.01
***	Significance Level: 0.001

1 Introduction

1.1 Background and Motivation

The process of investment and trading in financial markets is normally accompanied by the arrivals of news events containing important financial and economic information. In particular, the arrival of important news may result in sudden large changes and strong fluctuations in asset prices, since investors and traders would re-balance their portfolios according to the arriving news. Companies' cash flows and risk-adjusted discount rates are also affected by news events such as monetary policy announcements, see Hussain (2011). Additionally, the arrival of typical economic news events may depict future economic activity. However, the relationship between market reaction and news flow is still complex and ambiguous. The thesis studies two classes of important news—firm-specific and macroeconomic announcements—with the aim of investigating the impacts of these two types of announcements on jumps and variance of stock prices. Jumps, as abrupt large returns, and variance, measuring market fluctuations, are the two most important financial risk variables in risk management. A detailed research on the impact of these two classes of news on jumps and variance will substantially contribute to understanding and managing financial risks.

1.1.1 Jump in Financial Literature

There are always impressive facts from financial markets to investors. On October 9, 2007, the S&P 500 index positively changed by 10.49%. However, on June 27, 2008, it shocked the whole world with a negative return of 11.66%. Most investors suffered on this black day; nevertheless, black days seem to always recur and be darker than expected. On November 4, 2008, the S&P 500 index dropped 21.33%, reminding investors that everyone was already in a financial crisis.

Shockingly large changes in asset prices are by no means accidental phenomena. This can be seen in a large amount of empirical research and is documented as a stylized fact in the dynamics of stock prices. In the existing literature, researchers have aimed to answer two fundamental questions: theoretically, how to model jumps in asset prices properly, and empirically, how to detect jumps from market data.

For modeling jumps, Merton (1976) made a ground-breaking contribution to financial models in his seminal work. He introduced a Poisson process to the Black-Scholes model to generate discontinuous paths for the underlying asset. The motivation behind this idea was based on two stylized empirical observations in stock and option markets. First, the return of most assets follows a fat-tail law instead of a normal distribution; second, the implied volatility from market option prices demonstrates a smile curve with different strike prices. This contradicts the constant volatility in the Black-Scholes model. Adding

jumps to Brownian motion provides a solution to these problems. Following this idea, several diffusion jumps models have been developed in the finance literature. Colwell and Elliott (1993) considered a Markov diffusion with jumps. Bates (1996); Jiang (1999) modeled both jumps and stochastic volatility, and presented a detailed comparison for the impacts on option prices. Bates (2000) found empirically that jump models with stochastic volatility had a better fit to market option prices. Moreover, Kou (2002); Kou and Wang (2004) proposed an extension of Merton (1976) to a double exponential jump diffusion process. One prominent advantage of this model is the analytical solution to pricing options. Apart from jump-diffusion models, a more general jump process in finance that is becoming increasingly popular is the Lévy process. Geman (2002) stressed that pure jump Lévy processes with finite variation and infinite activity perform better than jump-diffusion in representing stock price dynamics. Carr et al. (2003) extended the Poisson processes in the Bates model to the Lévy process to jointly model stochastic volatility and Lévy jumps. Besides these continuous time jump models, jumps are also introduced in discrete time financial models to model non-Gaussian daily returns, see (Duan et al., 2006a; Maheu and McCurdy, 2004; Ornthanalai, 2014); for more details regarding jumps in financial models, see e.g., (Tankov, 2003).

In respect to detecting jumps, several detection test statistics have been developed. Barndorff-Nielsen and Shephard (2004) proposed a jump-robust integrated variance estimator, which is fundamental for constructing jump detection test statistics. Subsequently, Huang and Tauchen (2005) developed a jump test considering the ratio of jump robust integrated variance estimators to non-robust ones. Barndorff-Nielsen and Shephard (2006) presented asymptotic distribution for the above jump tests. Barndorff-Nielsen et al. (2006) extended bipower to a multipower case and investigated the limit behavior of multipower variation when the underlying semimartingale process presents jumps. Jiang and Oomen (2008) introduced an alternative detection method based on a statistic they named swap variance. Swap variance considers the difference between geometric and arithmetic returns. The main focus of Jiang's test is on the difference between swap variance and realized variance. Aït-Sahalia and Jacod (2009) introduced jump test statistics based on the scaled realized power variation, and they established the corresponding central limit theorem. Podolskij and Ziggel (2010) developed a test that can be applied to general semimartingale models. The construction relies on truncated power variation introduced by Mancini (2009). Another type of jump detection method relies on comparing returns and the estimated spot volatility. Widely applied examples of this method were provided by Andersen and Bondarenko (2007) and Lee and Mykland (2008). The only difference between the two tests is the selection of critical value. A detailed comparison for the power of these jump detection statistics is provided by Dumitru and Urga (2012), showing that the test conducted by Lee and Mykland (2008) is relatively powerful compared to other competitors. Additionally, Lee and Hannig (2010) provided a test effective to Lévy jump processes. More recently, Xue et al. (2014) proposed a new non-parametric test for jumps using wavelet decomposition. Regarding jump detection methods, two issues deserve attention. One is the impact of microstructure noise, which is discussed thoroughly by Bajgrowicz et al. (2015). The other is the intraday pattern in high-frequency asset prices. A related discussion and a robust estimation can be found in the work of Boudt et al. (2011).

1.1.2 Time-varying Variance in Financial Literature

Another essential fact in financial markets is fluctuation. Ongoing fluctuations in asset prices bring investors risks in their holding portfolios. Variance or volatility[1] of asset returns measures the fluctuation of asset prices, which is one of the most important factors in financial models. For instance, volatility plays a key role in option valuation, which is a unique parameter that is unobservable in the market. Variance is also crucial in financial risk management because it at least partially determines the distribution of risks.

Financial variance has several stylized facts: It is inconstant, clustering, and strongly autocorrelated (see Cont (2001); Teräsvirta and Zhao (2011)). To capture these characteristics, Engle (1982) first introduced autoregressive conditionally heteroscedastic (ARCH) models for modeling the inflation rate in the U.K.. Bollerslev (1986) generalized the ARCH models to include past conditional variance. Sequentially, various extensions in the form of GARCH models appeared (see Bollerslev et al. (1992); Engle (2010)). I briefly review some models in the GARCH family that are widely applied in the empirical literature. Nelson (1991) introduced the EGARCH model to study the persistence of shocks in conditional variance. Glosten et al. (1993) developed the GARCH-M model to allow an asymmetry impact from innovations on variance. This model is popular in the finance literature as the GJR model. Another widely used asymmetric GARCH model was introduced by Engle and Ng (1993) and is named NGARCH. The authors clearly documented the asymmetric shocks on variance through a news impact curve. Baillie et al. (1996) focused on modeling the strong autocorrelation in variance. The FIGARCH model produces a hyperbolic rate of decay in autocorrelation function. Component GARCH (CGARCH) was first introduced by Engle and Lee (1999) for separating the short component from long-run variance. Recently, a new GARCH model was introduced in the continuous time literature—namely, Klüppelberg et al. (2004) introduced the COGARCH model driven by a Lévy jump process.

Since GARCH models can effectively capture many stylized facts of asset returns, which are misspecified in the Black-Scholes model, many researchers have attempted to price options with GARCH models. In the framework of martingale pricing, the key is to specify a risk-neutral measure. Duan (1995) specified a risk-neutral probability measure through the "Local Risk Neutral Valuation Relationship" with Gaussian innovations. Another general specification is through conditional Esscher transform. Christoffersen et al. (2009) theoretically reviewed such a method to specify equivalent martingale measures with many popular GARCH models as examples. Furthermore, the authors confirmed that the risk-neutral measure is not unique due to market incompleteness. Christoffersen et al. (2013) specified a variance-dependent pricing kernel in the Heston-Nandi model introduced by Heston and Nandi (2000). The new pricing kernel yields a better explanation of the implied volatility puzzle. Moreover, Christoffersen et al. (2008) extended the CGARCH model in (Engle and Lee, 1999) and proposed a two-component GARCH model for option pricing. The model also produces a more realistic variance term structure. Apart from Gaussian innovations, several non-Gaussian GARCH models have been developed in the option pricing literature. Chorro et al. (2012) considered the generalized hyperbolic innovations nesting normal innovation as a special case. GARCH models with jumps have also been applied to valuate options (see Duan et al. (2006a); Ornthanalai (2014)). Realized variance estimated from intraday is jointly modeled with conditional variance of returns for option pricing in Christoffersen et al. (2014).

[1] In this research, volatility is defined as the square root of the variance of asset returns. Some literature refers to the variance of asset returns as volatility (e.g., Andersen et al. (2009)).

Finally, I would like to highlight four advantages of GARCH models with different purposes. First, GARCH models produce significant power to fit the stylized characteristics of asset returns. Second, compared with continuous time models (Bates, 1996; Heston, 1993), the parameters in GARCH models are relatively easy to estimate[2], because the full likelihood function is known. Third, the limit of some GARCH models is a stochastic volatility model with two diffusion factors. Lastly, and most importantly, GARCH models are fairly flexible to incorporate other economic factors. This is the main reason why I price options using GARCH models with news event data.

1.1.3 News Arrival Events in Financial Literature

Research on how news affects financial markets is becoming increasingly attractive to investors. Due to the variation in news content, I select some research related to certain types of news as follows.

According to the temporal property of information flows, news is labeled as either scheduled or non-scheduled. Lee (2012) investigated the predictability of large change in stock prices (jumps) using both scheduled macroeconomic information and non-scheduled news, such as analyst recommendations. Bradley et al. (2014) studied both scheduled and non-scheduled experts' recommendations to value the analysts' advice in the financial industry. News data were extracted from the Institutional Brokers' Estimate System (I/B/E/S).

In the finance literature, some research has focused on public and private news in a certain market. For example, DeGennaro and Shrieves (1997) estimated the impact of public and private news on exchange rate volatility (Japanese Yen vs. U.S. dollar). The public news they used were from Reuters news items including regularly scheduled macroeconomic news, unscheduled economic policy news, and unscheduled interest rate reports. However, the private information was measured as unexpected quote arrivals instead of direct observations from some data sources.

Macroeconomic news and firm-specific news are the most widely studied types of economic information in finance. Jones et al. (1998) examined the relationship between U.S. macroeconomic news and bond volatility. They considered employment news and producer price index. Kilian and Vega (2011) tested the impact of macroeconomic news on energy prices. Love and Payne (2008) showed how macroeconomic information is incorporated into prices through an order flow trading process.

The Securities and Exchange Commission (SEC) plays an important role in releasing news to financial markets. According to the SEC's regulations, news can be grouped into regulated and unregulated news. Regulated news is material, non-public information from a publicly traded company delivered to the public (see Mitra and Mitra (2011)). While news coming from other news media for the purpose of public trading business is called unregulated news, it is not controlled by the SEC.

From a data management viewpoint, the news can be classified as mixed high frequency news and seasonal announcements. Engle et al. (2011) used rather comprehensive microeconomic news data collected from the Dow Jones Intelligent Indexing system. Chan (2003) used the Dow Jones Interactive Publications Library of past newspapers, periodicals, and newswires.

[2]For parameter estimation in continuous time models, see e.g., Aït-Sahalia and Kimmel (2007) and Yang and Kanniainen (2017)

Finally, there are other classifications for news data applied in finance research. Interests can be absorbed in one industry, such as in Sabet and Heaney (2015). The authors tested information asymmetry around mergers and acquisitions of U.S. oil and gas companies. News can also be limited in one geographical area, as in the work of Baum et al. (2015), who studied the impact of Chinese macro announcements on the world economy.

Although it is consistent with our intuition and even supported by economic theory that financial markets are driven by news, formal discussion and cautious investigation based on real market data, econometric methods, and financial models are still necessary. This is also the target of this research.

1.2 Research Questions and Methodology

This thesis investigates the impact of firm-specific announcements and macroeconomic announcements on two of the most important financial risk variables—jumps and variance.

Regarding the impact of news on jumps, I aim to answer the following questions:

- Is there a statistical association between jumps in stock prices and the release of important news events in Nordic and U.S. markets?
- How can we measure the association between jumps in stock prices and news events?
- Do firm-specific scheduled and non-scheduled announcements contribute to jumps in Nordic markets? If so, what are the characteristics of jump sizes that associate to announcements?
- Does the Nordic market react to typical firm-level announcements, such as acquisition and changes in board composition, in terms of jumps?
- What are the contributions of U.S. macroeconomic announcements to jumps in both domestic and Nordic markets?

The answers to the questions above are obtained from high-frequency stock prices and news data including firm-specific and macroeconomic announcements. Econometric methods are strongly relied on. Specifically, non-parametric tests play an essential role in the statistical framework for comparing waiting times. Applying Lee's statistics (Lee and Mykland, 2008), I detect jumps in the S&P500 index and three Nordic stock markets: Finnish exchange, Swedish exchange, and Danish exchange. Nordic markets are focused in this thesis because first, to my best knowledge, there is little research discussing the impact of Nordic firm-level news events on jumps using high frequency equity prices; second, the available data sources at Tampere University of Technology provide a possible detailed investigation on Nordic markets; third, a comparison between relatively illiquid Nordic markets and liquid U.S. market can be drawn for examining the impact of news arrivals on jumps. To compare the empirical and simulated waiting times, which are between the arrival of announcements and the neighboring jumps, I apply the Kolmogorov-Smirnov (K-S) test to determine the equality and relative position between the distributions of empirical waiting times and their simulated reference. Additionally, I perform a Welch U test to compare the identities of sample means of waiting times. Bootstrapping is also tentatively implemented, particularly in Section 4.1, to examine the equality of medians between empirical waiting times and the simulated reference sample.

The construction of the reference waiting times of general announcements is undertaken via random simulation. First, the number of daily announcements following uniform distribution is simulated. In the second step, single announcement is sampled from the empirical distribution of the interested real news sample. To estimate empirical distribution, kernel smooth is applied if necessary.

On the impact of macroeconomic news on variance, I aim to answer the following questions:

- How can macroeconomic news impact be incorporated in GARCH models for option valuation?
- Does macroeconomic information explicitly improve GARCH models for fitting market data?
- Do standard GARCH models sufficiently capture the macroeconomic news events in terms of option valuation performance?

The econometric methods used in this part include dummy regression, quasi maximum likelihood estimation (QMLE), and simulation. First, to construct a reasonable comprehensive variable for the impacts of different types of macroeconomic releases, I consider the dummy variables of macro news announcement date, then I regress the realized variance on these dummy variables to extract the predictor of daily variance based on the arrival of macroeconomic news. The purpose here is to gain a macro news-based variable for daily variance instead of fitting realized variance perfectly to the macro news indicators.

Second, all parameters in the GARCH models are estimated using the QMLE method, which provides reliable parameter estimates even if the innovations are misspecified as standard normal variables. Furthermore, I consider the autocorrelation in the VIX-fitting error sequence and assume it follows an AR(1) process as in Kanniainen et al. (2014). In the optimization procedure for QMLE estimates, I follow the sequential optimization strategy suggested in Amado and Teräsvirta (2013), which Song et al. (2005) showed is efficient.

Finally, option valuation for all GARCH models with and without news impacts are realized by carrying out Monte Carlo simulation. To reduce variance in the simulation, I apply empirical martingale methods introduced in Duan and Simonato (1998) and antithetic variables.

1.3 Structure and Contributions of the Thesis

1.3.1 Structure of the Thesis

This thesis consists of seven chapters mainly focusing on discussing the impact of news events on *Jumps* and *Variance* respectively. The contents of each part are as follows:

Chapter 1 provides an overview of the thesis, including brief descriptions of the research motivation and objectives, as well as a review of the relevant financial models with jumps, jump detection methods, and GARCH models.

Chapter 2 develops a non-parametric framework in order to examine the association between economic announcements and asset prices statistically. Chapter 3 presents a

detailed description of high frequency stock prices and news announcements data from Nordic and U.S. markets.

Chapter 4 and 5 apply the statistical framework presented in Chapter 2 in order to analyze empirically the impact of firm-specific news events and U.S. macroeconomic announcements on Nordic and U.S. stock prices. In particular, Chapter 4 investigates the impact of scheduled and non-scheduled Nordic firm-specific announcements on Nordic stock prices. The sizes of jumps related to Nordic scheduled and non-scheduled firm-specific announcements are discussed. Moreover, the impact of selected important firm-specific announcements on Nordic stock prices is tested separately. Chapter 5 focuses on the impact of U.S. macroeconomic announcements on Nordic stock prices and also examines the impact of U.S. macroeconomic announcements on the U.S. stock index in term of jumps.

Chapter 6 investigates the contributions of macroeconomic news to equity variance modeling and the related option valuation performance with standard GARCH models.

Chapter 7 discusses the findings and presents the conclusions.

1.3.2 Contributions

1.3.2.1 A Nonparametric Statistical Framework

Chapter 2 of this research highlights the role of essential economic announcements in driving large changes in stock prices. The first main contribution of this thesis to the finance literature is its design of a non-parametric framework for statistically determining the link between announcements and jumps. Essentially, I compare the statistical characteristics of waiting times of real announcements with the simulated general reference.

First, I apply the statistical test introduced by Lee and Mykland (2008) to detect jumps. This method has two advantages which are crucial to the statistical framework. One is that the location of jumps can be detected and the other is that the method is non-parametric. The process of underlying asset only needs to satisfy several general assumptions.

Second, a detailed analysis of waiting times is an innovative perspective for studying the impact of announcements on jumps. There are several advantages of analyzing waiting times: **(1)** The waiting time between an announcement and jump directly measures the market reaction speed to the announcement. This allows for a more precise analysis than logistic regression analysis for predicting jumps on the basis of news arrival indicators (e.g., Lee (2012)). **(2)** Waiting times use timestamps, which are the only common numerical character of different economic announcements. Consequently, focusing on waiting times allows for analyzing the impact of both composite and single types of announcements, for example, scheduled announcements and FOMC (Federal Open Market Committee). Moreover, the statistical property of waiting times describes a fundamental stochastic relationship between announcements and the corresponding jumps in stock prices. This contributes to the literature on jumps (Lahaye et al., 2011; Lee and Mykland, 2008), which usually provides an informal conclusion that a certain jump is caused by some news simply because they are close in time. **(3)** I study both forward and backward waiting times. Forward waiting times correspond to the naturally causal order in which investors first obtain economic news, then change their trading strategies, and re-balance

their portfolio. As a result, jumps in stock prices are observed shortly after the news announcement. However, information asymmetry exists in all financial markets. Markets might pre-react to some news, especially non-scheduled announcements, in terms of jumps. In this case, backward waiting times would behave abnormally longer or shorter than the general trend. This implies the existence of information leakage. **(4)** The difference between using calendar time or trading time to calculate waiting times is discussed in detail. This consideration of the different effects of calendar time and trading time was initiated by Kanniainen and Yue (2017).

Third, in order to construct a reasonable reference sample for waiting times between a general class of news and neighboring jumps, reference event timestamps are simulated according to the sample size and empirical distribution of real announcements. A reasonable reference sample consists of independent news alerts with similar intraday patterns as real news events. In each iteration, the reference sample size is equal to the size of the real sample, and the number of daily announcements is uniformly distributed along the time horizon. Each single announcement is sampled from the empirical distribution of the concerned real news sample. The main advantage of this simulation strategy is that the disturbance of a strong intraday seasonal pattern can be eliminated. This procedure was introduced and first implemented by Prof. Juho Kanniainen in our joint work (Kanniainen and Yue, 2017) contributing to the event study literature with high-frequency data. In this joint work, I proposed the main idea of comparing the distribution and mean of waiting times and detected jumps in cleaned high frequency data. Prof. Juho Kanniainen developed a detailed specification for waiting times with reference timestamps sufficiently considering intraday pattern. Prof. Juho Kanniainen also prepared the main draft of Kanniainen and Yue (2017).

Lastly, non-parametric tests, such as K-S and Welch U-test, are applied. This, together with Lee's jump detection test (Lee and Mykland, 2008) makes the statistical framework widely applicable and robust to the specification of underlying asset dynamics and announcement flow.

1.3.2.2 Empirical Evidence in Nordic and U.S. Markets

A thorough empirical analysis of the influence of Nordic firm-specific and U.S. macroeconomic announcements on Nordic stock prices and SPY contributes to the empirical finance literature. The empirical research in sections 4.1 and 5.2.1 from Kanniainen and Yue (2017) was implemented by Prof. Juho Kanniainen. The rest of the empirical analysis was developed by Ye Yue, and the results are presented for the first time in this thesis.

The first interesting finding is that the Finnish, Swedish, and Danish markets all react actively to the arrival of scheduled firm-specific announcements. However, the reaction to non-scheduled announcement for Swedish stock prices is not statistically significant. There is no significant evidence showing that stock prices from all three markets jump before the announcement of scheduled and non-scheduled firm-specific news. This statistically implies that there is no strong leakage for either scheduled or non-scheduled information in Nordic markets. What is more, scheduled announcements contribute larger jumps than non-scheduled announcements on average in all three Nordic countries. Negative jumps are detected to be larger in both size and amount. Additionally, I examine the impact of five typical firm-specific announcements including acquisition, change in board composition, change in capital, company announcement, and interim report. Surprisingly, the release of an interim report is found to be the most important type of firm-level announcement to three Nordic markets in terms of causing jumps in stock prices. The

release of acquisition information also lead to jumps, but later than in the case of general announcements. The reactions to news on changes in board composition are different among the three Nordic markets. Finnish and Danish investors seem more sensitive to information on board changes of listed companies; however, this is not observed in the Swedish market. Company announcements are also found to be informative in the sense of leading jumps. Nevertheless, the observed large abnormal returns in the Nordic market are statistically not related to news on changes in capital. All these empirical results contribute to the literature on corporate financial risk management. By all means, these are good references on investors and traders' practices in Nordic markets.

U.S. macro announcements represent another class of important economic news. This research makes a contribution by discussing the impact of those U.S. macroeconomic releases on typical times. In particular, I examine the influence on Nordic stock prices. The announcements arriving at 1:00 p.m., 3:45 p.m., and 11:00 p.m. in Central European Summer Time (CEST) are found to affect the Nordic stock markets significantly in terms of jumps. This is a stylized fact regarding jumps in Nordic markets originating from the intraday pattern of U.S. macroeconomic releases. Similar findings on other European markets can be found in Hussain (2011). The author shows significant impact of several US macroeconomic variables on four European stock markets including Germany, France, Switzerland and the United Kingdom. Nikkinen et al. (2006) document that the G7 countries, the European countries other than G7 countries, Asian countries are significantly influenced by scheduled U.S. macroeconomic news.

Overall, I found strong evidence that jumps in stock prices can be driven by both past and forthcoming announcements. This empirical observation contributes to extending the existing jump models in risk management and option pricing. Investors and traders in Nordic markets may also benefit from the empirical results in this research in terms of understanding jumps and the impacts of domestic and foreign news.

1.3.2.3 Variance Modeling and Option Valuation with Macro Announcements

This part mainly contributes to the asset pricing literature investigating the impact of news on option valuation. The classical option pricing model only models the stochastic property of underlying assets. Under the assumption of no arbitrage in the market, a fair price can be guaranteed for an option contract. I attempt to incorporate the news factor into GARCH models to valuate option without breaking the risk-neutral pricing frame.

First, the macro news variables are constructed. In analyzing macro news impacts on jumps, I still consider only the macro news arrival timings. One feature of these macro releases is that their announcement times are normally scheduled one year in advance. This is crucial because the announcement time process is essentially foreseen; thus, including the impact of announcement time in GARCH models does not introduce more randomness, which might be against the martingale pricing principle. Besides simply considering the indicator of a certain type macro news arrival as a news impact variable, I use the predictor from the regression of realized variance on all selected macroeconomic announcements.

The main contribution in this part is that I identify a proper way of adding the news impact as a multiplier to the variance equation in GARCH models. There are at least three advantages of this design: first, an analytical VIX formula can be derived in this setting; second, the news-GARCH models nest their classical counterpart, and this makes

it possible to examine the impact of news variables on variance; third, it is straightforward and simple to implement Monte Carlo simulation for option pricing.

In the empirical work, I estimate parameters from return and VIX, and then I price European options and compare the pricing performance of different GARCH models with and without macro news impacts. I find that macroeconomic news releases play a minor role in explicitly modeling return and option valuation. This finding empirically answers the question that whether explicitly using macroeconomic releases really matter to option valuation, and it contributes to the empirical asset pricing research.

Kanniainen and Yue (2017) is the main reference for chapter 2, section 4.1 and section 5.2.1. I hereby declare that this thesis was composed by myself and that the work contained herein is my own except where explicitly stated otherwise in the text.

2 News Events and Jumps: A Nonparametric Statistical Framework

2.1 Jumps Detection

The introduction of jumps to the classical Black-Scholes model was first implemented in the seminal work of Merton (1976), who broke a key assumption that the path of underlying stock price is continuous by adding a Poisson process to the BS model. Along this line, Kou and Wang (2004) extended Merton's model to a double exponential jump diffusion process, under which there is also an analytical, tractable option pricing formula. Another class of popular models is that of stochastic volatility, which was designed to meet the time varying volatility. Bates (1996) considered both jumps and stochastic volatility and developed an efficient way to price American options. Additionally, Bates (2000) showed that stochastic jump models are a good fit for market option prices. For modeling volatility skewness and option prices, Carr et al. (2003) extended the Poisson processes in Bates' model to more general Lévy processes. For more details regarding jumps in financial models, see Tankov (2003).

From financial econometricians' viewpoint, these jump models are new challenges in terms of statistical testing. In the last decade, several important jump detection methods have been developed. Barndorff-Nielsen and Shephard (2004) first proposed an integrated variance estimator that is compatible with jumps. Huang and Tauchen (2005) developed a jump test as the ratio of jump robust integrated variance estimator to a non-robust one. Barndorff-Nielsen et al. (2006) extended bipower to the multipower case and investigated the limit behavior of multipower variation when the underlying semimartingale process presents jumps. Besides designing jump tests using realized variance or variation, Andersen and Bondarenko (2007) and Lee and Mykland (2008) considered the behavior of variance normalized return and designed test statistics of the ratio of return and estimated spot volatility. The only difference between the two tests is the selection of critical value. Aït-Sahalia and Jacod (2009) introduced jump test statistics based on scaled realized power variation, and they also established the corresponding central limit theorem.

In this chapter, I follow the jump detection method introduced in the work of Lee and Mykland (2008), which is one of the most commonly used methods in recent literature. The dynamic of the asset i log-returns is assumed to be driven by stochastic differential equation

$$d\log S_i(t) = \mu_i(t)dt + \sigma_i(t)dB_i(t) + Y_i(t)dJ_i(t) \tag{2.1}$$

where $B_i(t)$ is a Brownian motion. The jump component is $\int_0^t Y_i(s)dJ_i(s)$, which is assumed to be independent of $B_i(t)$. $Y_i(t)$ is the jump size, and $J_i(t)$ is a counting process independent of $B(t)$, such as a non-homogenous Poisson-type jump process. In fact,

Lee and Mykland (2008) argued that "scheduled (deterministic) events such as earnings announcements are allowed to affect jump intensity dynamically." This specification incorporates a sufficiently large class of asset price dynamic settings, like the stochastic volatility models in Heston (1993), Bates (1996), Schöbel and Zhu (1999), and the finite activity jump semi-martingale class in Barndorff-Nielsen and Shephard (2004).

The jump detection statistic introduced in Lee and Mykland (2008) is the log return normalized by volatility

$$\mathcal{L}_i(k) \equiv \frac{\log[S_i(t_k)/S_i(t_{k-1})]}{\widehat{\sigma}_i(t_k)}, \tag{2.2}$$

where

$$\widehat{\sigma}_i(t_k)^2 = \frac{1}{K-2} \sum_{j=k-K+2}^{k-1} |\log[S_i(t_j)/S_i(t_{j-1})]||\log[S_i(t_{j-1})/S_i(t_{j-2})]|, \tag{2.3}$$

$\widehat{\sigma}_i(t_k)$ is the square root of realized bipower variation for asset i at time t_k, which is a jump-robust estimator for instantaneous volatility (for more details, see Barndorff-Nielsen and Shephard (2004)). K is the window size for calculating the bipower variation. The authors suggested K = 156 for a 15-minute sample of stock prices.

Intuitively, if stock prices jump within the interval k, then the size of the normalized return $\mathcal{L}(k)$ should be significantly larger than a general level when there were no jumps. Lee and Mykland (2008) showed that if there are no jumps in the stock price process, then

$$\frac{\max_{i\in\{1,\ldots,n\}} |\mathcal{L}_i(k)| - C_n}{T_n} \longrightarrow \xi \tag{2.4}$$

where

$$C_n = \frac{(2\log n)^{1/2}}{\sqrt{2/\pi}} - \frac{\log\pi + \log(\log n)}{2\sqrt{2/\pi}(2\log n)^{1/2}}, \quad T_n = \frac{1}{\sqrt{2/\pi}(2\log n)^{1/2}},$$

n is the sample size and ξ has a standard Gumbel distribution, $P(\xi \leq x) = \exp(-e^{-x})$. Consequently, the following rejection region is obtained for the null hypothesis (absence of jump within the kth time interval):

$$\frac{|\mathcal{L}_i(k)| - C_n}{T_n} > -\log(-\log(1-\alpha)),$$

α is the level of significance.

2.2 A New Statistical Framework

The detected jumps (abnormal large returns), as a widely observed empirical stylized fact of asset prices, need an economic interpretation. Considerable research has linked jumps to news items (see Lahaye et al. (2011) and Lee (2012)). However, there appears to be little research into whether certain announcements can be associated with jumps that precede or follow the announcements in a statistical sense.

The purpose of this research is to develop a statistical framework for analyzing whether the times of the detected jumps are abnormally distributed before and after an economic or company announcement. In particular, I aim to answer the following question statistically: Does the market react to announcements in terms of jumps?

The association between news arrivals and detected jumps is tested via the *time distance* between a detected jump and an announcement. This distance can be either forward or backward. Forward distance measures the speed of new information being adapted to stock prices, whereas backward distance reveals the markets' pre-reactions, which may result from possible information leakage. Backward and forward time distances between announcements and detected jumps are also referred to as "waiting time" in this research.[1]

Intuitively, for a given announcement, the shorter the forward waiting time for a jump, the faster informed investors trade according to such an information shock. In the sense of market effectiveness, forward waiting time distance can be used to assess the importance of an announcement to the financial markets. If a set of announcements is not considered very new and important, the investors would not change their trading strategies accordingly. As a result, no jumps tend to be observed from the market in a short period. Nevertheless, backward waiting time distance relates to information leakage in the market. Stock prices could pre-jump even some days ahead of forthcoming announcements in the case of "channeled" information leakage. Therefore, there will not necessarily be other jumps observed in the following days due to that announcement. Backward distances can be used to analyze (i) potential information leakage with non-scheduled news whose arrivals are unpredictable or (ii) how markets pre-process information about forthcoming scheduled news with only predictable arrival times, but non-predictable contents.

In order to study and test the statistical association between a certain set of announcements and the detected neighbor jumps, I introduce and implement a non-parametric statistical framework. With the framework, the distribution of the empirical waiting times around announcements is compared to the distribution of sampled reference data representing the general properties of jump dynamics. Additionally, high frequency stock prices show significant intraday seasonality patterns, which are sufficiently taken into account in this study. I concentrate on the properties of cumulative distribution function (CDF) of waiting times. If the CDF of the observed waiting times around the empirical announcements is significantly above the CDF obtained with the reference data, then the announcements can be said to make an abnormally high contribution to the (detected) jumps.

2.2.1 Forward and Backward Time Distances

I first define forward and backward distances (waiting times). The observed forward time distance d^+ is the time between an announcement and the first detected jump that follows. The observed backward time distance d^- is the time between an announcement and the latest detected jump that precedes the announcement. Generally, d without a superscript refers to d^+ and d^-.

In detail, let $a_{i,k}$ be kth announcement timestamp associated with stock i and $p_{i,m}$ be the mth timestamp for stock i. I detect a jump in each time interval $[p_{i,1}, p_{i,2}), [p_{i,2}, p_{i,3}), \ldots$. Moreover, let $\mathcal{T}_i$ be the set of beginning points of the intervals with detected jumps; that is, there is a jump detected in $[p_{i,m}, p_{i,m+1})$ if and only if $p_{i,m} \in \mathcal{T}_i$. Additionally, $\mathcal{T}_{i,k}^+$ denotes the set of beginning points of jump intervals that end after the arrival of the kth announcement, and $\mathcal{T}_{i,k}^-$ represents the set of beginning points of jump intervals that end no later than the arrival of the kth announcement.

[1] Backward (forward) time distance can be considered as waiting time from a detected jump (an announcement) to an announcement (a detected jump). The terms "time distance" and "waiting time" are used interchangeably in this thesis.

This leads to the following:

- $\mathcal{T}_{i,k}^{+} \cup \mathcal{T}_{i,k}^{-} = \mathcal{T}_i$ and $\mathcal{T}_{i,k}^{+} \cap \mathcal{T}_{i,k}^{-} = \emptyset$,
- and given that $p_{i,m} \in \mathcal{T}_i$, $p_{i,m} \in \mathcal{T}_{i,k}^{+}$ if and only if $p_{i,m+1} > a_{i,k}$; otherwise $p_{i,m} \in \mathcal{T}_{i,k}^{-}$.

Let $p_{i,h} \in \mathcal{T}_{i,k}^{+}$ be the beginning point of the *nearest* interval *with a detected jump* that *follows* the kth announcement; that is, $p_{i,h} = \min\left(\mathcal{T}_{i,k}^{+}\right)$. By definition, this jump interval $[p_{i,h}, p_{i,h+1})$ ends after announcement timestamp $a_{i,k}$, but can begin before $a_{i,k}$. The waiting time from the announcement timestamp $a_{i,k}$ to the beginning of the jump interval $p_{i,h}$ is defined as the forward distance:

$$d_{i,k}^{+} = \max\left(p_{i,h} - a_{i,k}, 0\right). \tag{2.5}$$

If the jump interval strictly follows the announcement timestamp—that is, $p_{i,h} > a_{i,k}$—then $d_{i,k}^{+} > 0$. However, note that the announcement timestamp can be within the associated jump interval, $p_{i,h} \leq a_{i,k} < p_{i,h+1}$. In this case, $d_{i,k}^{+} = 0$, which means a jump is detected within the same interval with the announcement arrival. However, we do not know whether the actual jump took place exactly before or after the announcement timestamp.[2] Therefore, forward distance measures the market reaction (in terms of jumps) that has taken place during an interval after or at the arrival of an announcement. This and other cases are demonstrated in Figure 2.1.

Now, let us define backward waiting time distance in detail. Let $p_{i,h} \in \mathcal{T}_{i,k}^{-}$ be the beginning point of the *nearest* interval *with a detected jump* that *precedes* the kth announcement; that is, $p_{i,h} = \max\left(\mathcal{T}_{i,k}^{-}\right)$. By definition, this jump interval $[p_{i,h}, p_{i,h+1})$ begins before the announcement timestamp and cannot end after the announcement timestamp $a_{i,k}$. The waiting time from the end of the jump interval $p_{i,h+1}$ to the announcement timestamp $a_{i,k}$ is defined as the backward distance:

$$d_{i,k}^{-} = a_{i,k} - p_{i,h+1}. \tag{2.6}$$

The backward distance is always non-negative because, by definition, $a_{i,k} \geq p_{i,h+1}$ if (and only if) $p_{i,h} \in \mathcal{T}_{i,k}^{-}$. Therefore, regarding backward distances, the actual jump has not taken place after the arrival of the announcement. The backward distance cannot accidentally measure the market's post-reactions. This feature is very important for using backward distances to examine market pre-reactions to information arrival.

2.2.2 Measure Waiting Time Distances

This section discusses how to treat non-trading hours for measuring waiting times. To measure waiting time distances, I first include the announcements that arrived on the business day during trading and non-trading hours. Second, because the waiting times are measured in terms of the trading time, the actual length of waiting time is no longer than the calendar time distance between the announcement timestamp and jump. Suppose that there is a non-trading period between an announcement and a jump such that news

[2] Notice that the jump detection methods determine *intervals* within which there are jumps with a given confidence level in the stock price rather than exact jump time stamps.

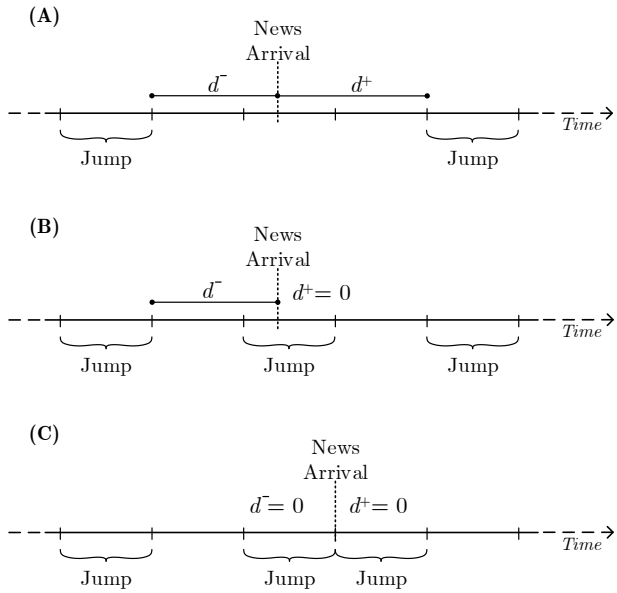

Figure 2.1: Plot A demonstrates the determination of forward and backward distances, d^+ and d^-, when the distances to the nearest jump periods are greater than zero. In plot B, the announcement timestamp is within a jump interval, and thus, $d^+ = 0$ (see Eq. 2.5), whereas d^- is greater than zero. Plot C demonstrates a hypothetical case in which the arrival of the announcement takes places *exactly* between two associated subsequent jump intervals, in which case, $d^+ = 0$ and $d^- = 0$.

arrival time is t, a related jump interval begins at s, a non-trading period begins at τ_1 and ends at τ_2, where $t < \tau_1 < \tau_2 < s$, and the length of the jump interval is Δs. Then the forward distance in terms of the trading time equals

$$(\tau_1 - t) + \Delta s + (s - \tau_2),$$

whereas the forward distance measured in calendar time would simply be $s - t$. If an announcement arrives during non-trading hours—that is, $\tau_1 < t < \tau_2 < s$—then the forward distance equals

$$\min(\Delta s, \tau_2 - t) + (s - \tau_2).$$

That is, in this case, the distance from the announcement to the opening time is never longer than the length of the jump period. The backward distances are calculated in the similar way. The advantage of including announcements delivered during non-trading hours is that it enlarges the sample size. For instance, the scheduled announcements from the Danish data set comprise 338 observations, but only 156 of them were published during trading hours. It is also reasonable to use only trading hours to measure time distances, since the use of actual (calendar) hours with non-trading time announcements can be problematic for measuring the market's reaction time. The lower bound of the market's reaction time can be several hours. For instance, if an announcement is released in the late afternoon, only a few minutes before the closing time, say at 3:58 p.m., and the market has no time to react to the announcement during the same day. Then it is reacted to the following morning around opening time, say at or slightly after 9:30 a.m., in which case the calendar time distance cannot be less than 17.5 hours. Therefore, last-minute cases are treated as the same as announcements published around the opening

time. It is worth noting that several announcements arriving during non-trading hours during the same night are all equally associated with the next jump. This may change the distribution property if there are massive announcements made on the same night. Consequently, the effect of "overnight trading" for different announcements is equally controlled by this approach[3].

2.2.3 The Reference Waiting Time Distance Samples

If jumps are associated with the arrival of announcements in terms of waiting time distances, we can expect that the market reacts to these announcements faster than to other unrelated general news. In other words, the waiting time for jumps associated with real announcements should be shorter than those related to other unrelated general news. However, it is essential to first define what "other unrelated general news" is. In fact, other unrelated general news can be understood as any news event that does not contribute to large changes in stock prices. Investors view these news events as invalid and will not change their trading strategies accordingly. For simulation, the unrelated general news need not be real information from the market. Regarding the arrival of a set of unrelated general announcements, I select a set of timestamps randomly. Randomness guarantees that the generated timestamps and related waiting times are general and independent of the empirical news announcements.

One straightforward way is to simulate the reference sample of timestamps of "unrelated, general news" uniformly in the time horizon. However, it might be pragmatic due to the strong intraday seasonality of jumps and the arrivals of announcements as well (see Lee (2012); Lee and Mykland (2008)). Consider a hypothetical example of the arrival times of certain types of announcements over multiple days mostly clustering in the first trading hour (data set A) and the others, arriving on multiple days, typically being delivered at around noon (data set B). In contrast, assume that jumps occur with a strong intraday seasonal pattern. For example, most jumps typically occur during the first trading hour, illustrating that the market reacts to the news that arrived after the closing time. Therefore, jumps around noon are clearly unusual. Consequently, if the reference data samples are generated from uniform distribution for announcement sets A and B without concerning the announcements' actual and different seasonal patterns, the association between the announcements and jumps is likely to be overestimated for data set A and underestimated for data set B.

Different types of announcements are of different intraday seasonal patterns that can be resolved by generating reference data sets with an empirical distribution of the arrival times of the announcements. In this thesis, timestamps associated with a specific asset (company) in the reference data sets are randomly sampled from the same asset's empirical distribution of the announcements. Considering the variation in the clock times of the arrival of announcements, kernel density estimation can be implemented for data smoothing. Following Botev et al. (2010), I optimize the bandwidth for irregularly arriving (company) announcements.[4] Once the arrival of the announcement is fixed to (a) specific timestamp(s), such as some macroeconomic announcements, the empirical distribution can be applied directly.

[3]There are also other measures for waiting times constructed considering calendar hours, see Kanniainen and Yue (2017). Related results are available by request.

[4]Their Matlab package is available on the MathWorks webpage: www.mathworks.com/matlabcentral/fileexchange/14034-kernel-density-estimator.

After sufficiently examining intraday seasonal patterns, I statistically compare distributions of (i) the empirical forward and backward distances between the actual arrival of news and the detected jump intervals, d^+, d^- and (ii) the forward and backward distances between generated reference timestamps and detected (empirical) jumps, $\tilde{d}^+, \tilde{d}^-$, respectively.

2.2.4 Procedure for Reference Data Sampling

I denote the trading days (observed from the empirical data) for asset i, $i = 1, 2, \ldots, N$, by a sequence of integers $\{T_{i,1}, T_{i,2}, \ldots, T_{i,m_i}\}$, where m_i is equal to the number of asset i's trading days in the data. $T_{i,j}$ represents the beginning (i.e., midnight, 00:00 a.m.) of day j (ref. `datenum` in `Matlab`). Following the date convention in Matlab, the length of one calendar day is one. Then the specific clock times on specific dates could be denoted by a floating number; for example, $T_{i,j} + 0.75$ would be day j at 6 p.m. In addition, for asset i, series $\{n_{i,1}, n_{i,2}, \ldots, n_{i,m_i}\}$ denotes the number of announcements assumed to arrive on days $\{T_{i,1}, T_{i,2}, \ldots, T_{i,m_i}\}$, $j = 1, 2, \ldots, m_i$.

A reference sample is generated as follows:

1. First, for asset i, I sample $\{n_{i,1}, n_{i,2}, \ldots, n_{i,m_i}\}$ from a discrete uniform distribution satisfying $\sum_{j=1}^{m_i} n_{i,j} = n_i$. $\{n_{i,1}, n_{i,2}, \ldots, n_{i,m_i}\}$ are associated with days $\{T_{i,1}, T_{i,2}, \ldots, T_{i,m_i}\}$, where $n_{i,j}$ corresponds to the number of timestamps on the jth day for asset i in the *reference data set*. n_i is the total number of empirical announcements considering both trading and non-trading hours.

2. Second, for asset i on trading day $T_{i,j}$, $n_{i,j}$ timestamps, $\{\tau_{i,j,1}, \tau_{i,j,2}, \ldots, \tau_{i,j,n_{i,j}}\}$ are independently sampled from an *empirical distribution* taking the intraday seasonality into account. The empirical distribution can be either asset-specific or using aggregated data over all the assets from the data sample. Kernel density estimation can be applied for data smoothing.

   Here, $0 \leq \tau_{i,j,k} \leq 1$ for $i = 1, 2, \ldots, N$ $j = 1, 2, \ldots, m_i$, and $k = 1, 2, \ldots, n_{i,j}$. Moreover, as specified above, $T_{i,j}$ is 00:00 a.m. $T_{i,j} + 1$ is 24:00 p.m. on the jth day, and therefore, given that $n_{i,j} > 0$, the generated timestamps for the ith asset and the jth day are $\{T_{i,j} + \tau_{i,j,1}, T_{i,j} + \tau_{i,j,2}, \ldots, T_{i,j} + \tau_{i,j,n_{i,j}}\}$. I repeat this step for all the trading days with positive $n_{i,j}$, $j = 1, 2, \ldots, m_i$.

3. Third, steps 1 and 2 are repeated for all N assets.

4. Then I apply the data processing described in Section 2.2.2. In particular, I make (i) the distance from the closing time to the arrival of news, (ii) the distance from the arrival of the news to the opening time of a trading day, and (iii) the length of the non-trading periods equal to no more than the distance of the jump period, after which the distances with the empirical and reference data sets are measured in trading hours.

5. Finally, steps 1−4 can be iterated to generate multiple reference samples.

2.2.5 Statistical Analysis of Waiting Times

Following the intuition that the forward distances of important announcements can be expected to be abnormally shorter than what they generally are, it is reasonable to postulate that the probability of the waiting time being less than or equal to x hours tends

to be larger with empirical announcement data than the general case. That is, $P(d^+ \leq x) > P(\tilde{d^+} \leq x)$, where d^+ refers to the distances between the empirical announcement times and the detected jumps and the $\tilde{d^+}$ distances between the generated timestamps and the detected (empirical) jumps. However, the analysis of possible information leakages through backward distances can methodologically be more complicated. The time information leakage taking place fundamentally determines the backward distance. It can be short or several days before the actual time of the announcement due to the complex manner of leakage. Additionally, if the leakage efficiently reduces the information asymmetry among the market participants and there are no other important news releases, then there will be no other jumps in the following days. This suggests, especially for backward distances, the necessity to separately test whether the empirical CDF is larger or smaller than the reference CDF. Therefore, I test the null hypothesis against two alternative hypotheses: (i) $P(d^- \leq x) > P(\tilde{d^-} \leq x)$ and (ii) $P(d^- \leq x) < P(\tilde{d^-} \leq x)$.

2.2.5.1 Kolmogorov-Smirnov Test

Two-sample goodness-of-fit tests are appropriate for testing the empirical distances against the generated reference distances to analyze the contribution of a set of announcements to the jumps. In this research, I adopt the one-sided two-sample Kolmogorov-Smirnov test, although other global non-parametric tests can also be applied for the same purpose.

Suppose we are interested in comparing the statistical properties of two samples, $\mathcal{X} = \{x_1, x_2, ..., x_m\}$ and $\mathcal{Y} = \{y_1, y_2, ..., y_n\}$. where $\mathcal{X}$ and $\mathcal{Y}$ are continuous and IID. It is reasonable to investigate and compare their probability distributions, $F^x(s) = P(x_i \leq s)$ and $F^y(t) = P(y_i \leq t)$, which summarize all of the random information in the samples. The Kolmogorov-Smirnov statistic only focuses on the empirical distributions of $\mathcal{X}$ and $\mathcal{Y}$, $F^x_m(s;\omega)$ and $F^y_n(t;\omega)$, where

$$F^x_m(s;\omega) = \frac{1}{m}\sum_{i=1}^{m} \mathbb{1}(x_i(\omega) \leq s), s \in R \tag{2.7}$$

$$F^y_n(t;\omega) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}(y_i(\omega) \leq t), t \in R \tag{2.8}$$

Here $\mathbb{1}(\cdot)$ denotes the indicator function. The empirical distribution function $F^x_m(s;\omega)$ is a good approximation of the distribution function $F^x(s)$, which follows the law of large numbers

$$F^x_m(s;\omega) \xrightarrow{P} F^x(s),\ \forall s \in R, m \to \infty \tag{2.9}$$

To compare the distribution functions, the one-sided and two-sided large deviations in empirical distributions are considered

$$D_{m,n}(\omega) = \sup_{t \in R} |F^x_m(t;\omega) - F^y_n(t;\omega)| \tag{2.10}$$

$$D^+_{m,n}(\omega) = \sup_{t \in R}(F^x_m(t;\omega) - F^y_n(t;\omega)) \tag{2.11}$$

Kolmogorov (1933) and Smirnov (1939) derived the following limit distributions for $D_{m,n}$

and $D^{+}_{m,n}$,

$$\lim_{m,n\to\infty} P\left(\sqrt{\frac{mn}{m+n}}D_{m,n} \leq d\right) = 1 - 2\sum_{k=1}^{\infty}(-1)^{k-1}e^{-2k^2d^2},\ d > 0 \tag{2.12}$$

$$\lim_{m,n\to\infty} P\left(\sqrt{\frac{mn}{m+n}}D^{+}_{m,n} \leq d\right) = 1 - e^{-2d^2},\ d > 0 \tag{2.13}$$

which provide the possibility to test the following two-sided hypothesis

$$\begin{aligned} H_0 &: F^x(s) = F^y(s),\ \text{for all } s \\ H_a &: F^x(s) \neq\ F^y(s),\ \text{for some } s \end{aligned}$$

with statistic $D_{m,n}$ and reject region $D_{m,n} \geq c_\alpha$.

For one-sided hypothesis,

$$\begin{aligned} H_0 &: F^x(s) = F^y(s),\ \text{for all } s \\ H_a &: F^x(s) \geq\ F^y(s),\ \text{for all } s,\ F^x(s) >\ F^y(s),\ \text{for some } s \end{aligned}$$

statistic $D^{+}_{m,n}$ is applied and the reject region is $D^{+}_{m,n} \geq c_\alpha$, where c_α is a positive critical number and, α denotes the significance level. More details on K-S test can be found in Durbin (1973) and Gibbons and Chakraborti (2011).

With the data collected from financial markets, I test whether the cumulative distributions of waiting times—that is, the forward and backward distances specified in Eq.(2.5) and (2.6)—are statistically larger or smaller between the empirical and generated reference timestamp data sets by K-S test, whose two assumptions are satisfied for the empirical analysis in this research. First, either waiting times or normalized jump sizes are continuous random variables. Second, the sample of waiting times or jump sizes associated with "real announcements" and their simulated references are mutually independent due to the procedure (Step 1 and 2) of the construction of reference sample in section 2.2.4. This procedure also guarantees the independence within the sample of reference data. The independence of elements in the sample of "real announcements" is assumed based on the following considerations: I randomly mix the target announcements from all large-cap companies in one market. Additionally, the waiting times or normalized jump sizes are associated to jump processes, which are assumed to have independent increments in the assumption of Eq. 2.1.

On the size of the reference sample, Bera et al. (2013) suggested that in a two-sample test, the reference sample should be larger than the sample to be examined, and they obtained satisfactory results with two-sample tests with the simple rule of thumb that the number of observations in the reference sample equals the squared number of observations in the test sample used. Therefore, in the context of this thesis, this would suggest that the data generations for the reference distribution should be iterated as many times as the number of empirical announcements observed in the data. Since the size of an empirical sample is $n = \sum_{i=1}^{N} n_i$, where n_i is the number of actual (empirical) announcements of asset i and N is the number of assets, n individual copies of the reference data sample (each with different random seeds) are generated.

2.2.5.2 Welch U Mean Test

Another natural idea is to compare the sample means and/or medians of the empirical and reference waiting times. However, the distributions of waiting times are normally asymmetric, the variances are unequal, and the sample sizes are different.

To compare the means of such two samples, $\mathcal{X} = \{x_1, x_2, ..., x_m\}$ and $\mathcal{Y} = \{y_1, y_2, ..., y_n\}$, where $\mathcal{X}$ and $\mathcal{Y}$ are only assumed to be continuous and IID, I adopt Welch's U-test, often called an unequal variances t-test for ranks of the data, to test the equality of means. The hypothesis with two-sided alternative is as follows:

$$H_0 : \mu^x = \mu^y$$
$$H_a : \mu^x \neq \mu^y$$

The hypothesis with one-sided alternative is as follows

$$H_0 : \mu^x = \mu^y$$
$$H_a : \mu^x < \mu^y$$

where μ^x and μ^y are the means of x_i and y_i respectively. Welch (1938) proposes a test statistic that is named "Welch U mean test",

$$U = (\bar{x} - \bar{y}) / \sqrt{\frac{S_x^2}{m} + \frac{S_y^2}{n}} \tag{2.14}$$

where $\bar{x} = \frac{1}{m}\sum_{k=1}^{m} x_k$, $\bar{y} = \frac{1}{n}\sum_{k=1}^{n} y_k$, and $S_x^2 = \frac{1}{m-1}\sum_{k=1}^{m}(x_k - \bar{x})^2$, $S_y^2 = \frac{1}{n-1}\sum_{k=1}^{n}(y_k - \bar{y})^2$. U is proven to be asymptotically t-distributed with f_U degrees of freedom,

$$f_U = \left(\frac{S_x^2}{m} + \frac{S_y^2}{n}\right)^2 \Bigg/ \left(\frac{S_x^4}{m^3 - m^2} + \frac{S_y^4}{n^3 - n^2}\right) \tag{2.15}$$

The standard Welch U mean test assumes that sample $\mathcal{X}$ and $\mathcal{Y}$ are distributed normally. This limits the application of the test largely. To relax this assumption, I follow the methodology in Fligner and Policello (1981). Instead of directly applying the Welch U mean test to sample $\mathcal{X}$ and $\mathcal{Y}$ (waiting times in this research), I tested and compared their ranks $\mathcal{R}^x = \{R_1^x, R_2^x, ..., R_m^x\}$[5], and $\mathcal{R}^y = \{R_1^y, R_2^y, ..., R_m^y\}$. This procedure is robust when the sample distributions are skewed with unequal variances. The performance of this mean test is investigated through Monte Carlo simulation and recommended in Fenstad and Skovlund (1992) and Fagerland and Sandvik (2009).

I also consider the statistical equality of medians via bootstrapping. Bootstrapping allows for generating a considerably large number—say 10,000—of reference data sets, whose sizes are the same as the size of the empirical data set. The left-sided (right-sided) p-value is then simply obtained by dividing the number of cases where the reference median is less (more) than or equal to the empirical median by the total number of reference data sets (say 10,000). The same bootstrapping procedure can be applied to p-values for the means.

[5] Consider the ordered sample $x_{(1)} < x_{(2)}, ..., < x_{(m)}$, if $x_i = x_{(R_i^x)}$, then R_i^x is defined as the rank of x_i

2.3 A Simulation Study

This section demonstrates the procedure of the nonparametric statistical framework introduced in section 2.2 via a simulation study. Intraday stock prices and the timestamps of news announcements are simulated based on the Bates model, then the test procedure is implemented on waiting times.

2.3.1 Simulate Stock Prices and Detect Jumps

In the simulation study, I assume that the stock prices follow Bates model, which was first introduced in Bates (1996). This model combines the Heston stochastic volatility model (Heston, 1993) with Poisson jumps. Consequently, the model is sufficiently flexible to capture stylized facts in financial markets, such as non-constant volatility and sudden large changes in stock prices.
The Bates model is

$$dS_t = \mu S_t dt + \sqrt{v_t} S_t dB_t^1 + S_t dZ_t \tag{2.16}$$

$$dv_t = \kappa(\theta - v_t)dt + \sigma\sqrt{v_t} dB_t^2 \tag{2.17}$$

where S is the stock price, v is the volatility process. $B = (B^1, B^2)$ is a correlated Brownian motion with the correlation parameter ρ. Z is a compound Poisson process with intensity λ, and the jump sizes follow the normal distribution $N(\mu^J, \sigma^J)$. Moreover, Z and B are assumed to be independent. κ, θ and σ are parameters with values 8, 0.05,and 0.343 respectively. $\mu = \widetilde{\mu} - \lambda(\exp(\mu^J) - 1)$, where $\widetilde{\mu} = 0.01$. The parameter values refer to (Bates, 1996) with adjustments. I simulate the 15-min prices of five stocks within four years. The selected discretization scheme is Euler-Milstein. For more details, see (Peter E. Kloeden, 1997).

Following the jump detection method in (Lee and Mykland, 2008), I detected the jumps in each simulated paths of stock prices and compared the overlap rates of the real jumps and detected jumps.

Table 2.1: Numbers of detected jumps, simulated jumps and Jaccard Rate for the simulated paths of five stock stocks.

	S_1	S_2	S_3	S_4	S_5
# Detected Jumps	778	750	723	757	769
# Simulated Jumps	967	926	897	948	948
Jaccard Rate	0.80455	0.80994	0.80602	0.79852	0.81118

Table 2.1 compares the numbers of detected jumps and simulated jumps for five stocks. The number of detected jumps is observed smaller than the simulated "real" jumps for all of the simulated stocks based on the Bates model. From the reported Jaccard rates[6], The jump detection method from Lee and Mykland (2008) captured approximately 80% jumps in this Monte Carlo simulation study. This is acceptable and accurate in practice.

[6]The Jaccard rate of two sets A and B is defined as $\#(A \cap B)/\#(A \cup B)$, the number of elements in the intersection set over the number of elements in the union set. The Jaccard rate is often used to measure the similarity of two sets.

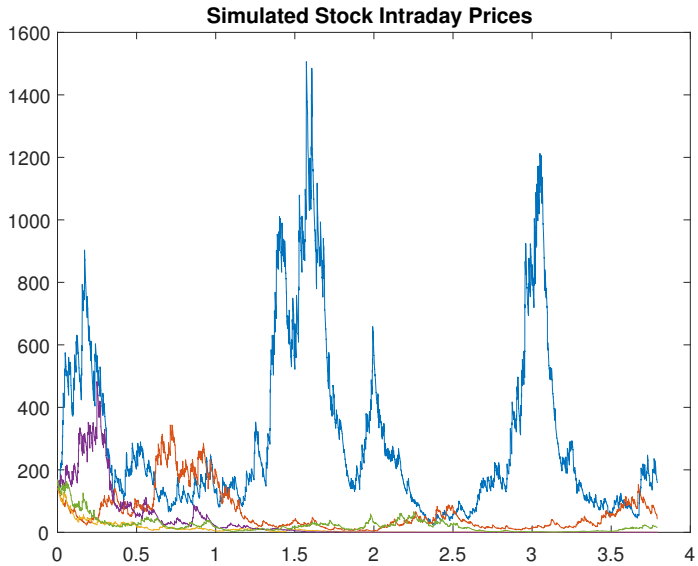

Figure 2.2: Five simulated paths of stock prices based on the Bates model (Bates, 1996) within four years. Starting points $S_0 = 150$, $v_0 = 0.05$. Parameters are set as $\kappa = 8, \theta = 0.05, \sigma = 0.343, \rho = -0.77, \lambda = 250, \mu^J = 0.06,$ and $\sigma^J = 0.1$. $\mu = \widetilde{\mu} - \lambda(\exp(\mu^J) - 1)$, where $\widetilde{\mu} = 0.01$. The step size is 1.14E-04 (15 minutes)

.

2.3.2 Simulate the Arrival of Announcements and Statistical Tests

To illustrate the effect of the nonparametric statistical framework in section 2.2, I considered a plain case for the arrival of news announcements. I simulated the timestamps of the news announcements, which are both uniformly distributed on the horizon and independent from the jumps in stock prices. This setting implies that the arriving news events are quite general and plain. Intuitively, the arrival of these news events should not stimulate markets and generate jumps in stock prices. Consequently, we can expect that the statistical properties of waiting times between simulated "real new events", $\mathbf{d}$, should be similar to its reference $\tilde{\mathbf{d}}$.

Table 2.2: Two-sample Kolmogorov-Simirnov and Welch U tests for Simulated Data. Testing whether the simulated empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Test the equality of means between the two samples. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 and 48 hours on both sides.

Panel A: Forward Distances

a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
#Obs of d	**#Obs of $\tilde{d}$**	**#Obs of d**	**#Obs of $\tilde{d}$**	**#Obs of d**	**#Obs of $\tilde{d}$**
1309	1709554	1248	1555008	470	220430
Mean of d	**Mean of $\tilde{d}$**	**Mean of d**	**Mean of $\tilde{d}$**	**Mean of d**	**Mean of $\tilde{d}$**
10.32	10.59	10.25	10.59	9.873	10.54
Welch U-test p left tail	**Welch U-test p right tail**	**Welch U-test p left tail**	**Welch U-test p right tail**	**Welch U-test p left tail**	**Welch U-test p right tail**
0.65	0.35	0.25	0.75	7.395E-02	0.93
h_a: larger	**h_a: smaller**	**h_a: larger**	**h_a: smaller**	**h_a: larger**	**h_a: smaller**
0.30	0.29	0.31	0.80	0.10	0.95

Panel B: Backward Distances

a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
#Obs of d	**#Obs of $\tilde{d}$**	**#Obs of d**	**#Obs of $\tilde{d}$**	**#Obs of d**	**#Obs of $\tilde{d}$**
1309	1709554	1248	1555008	470	220430
Mean of d	**Mean of $\tilde{d}$**	**Mean of d**	**Mean of $\tilde{d}$**	**Mean of d**	**Mean of $\tilde{d}$**
11.98	11.89	11.38	11.77	12.19	11.58
Welch U-test p left tail	**Welch U-test p right tail**	**Welch U-test p left tail**	**Welch U-test p right tail**	**Welch U-test p left tail**	**p right tail**
0.39	0.60	0.10	0.89	0.69	0.30
h_a: larger	**h_a: smaller**	**h_a: larger**	**h_a: smaller**	**h_a: larger**	**h_a: smaller**
0.30	0.63	0.21	0.95	0.85	0.21

Table 2.2 reports the P-values of the K-S and Welch U tests for both forward and backward waiting times of the simulated data. Due to the strategy of news events simulation, all of the tests showed an insignificant relationship between simulated news events and detected jumps. This is consistent with our expectations. As a result, this simulation study demonstrates that the nonparametric statistical framework is effective on examining the impact of news arrivals on jumps in terms of comparing the statistical characters of waiting times.

3 Descriptive Statistics on Jumps and Announcements

This chapter describes the high frequency stock prices data in three Nordic and U.S. markets. The influence of possible microstructure noise is demonstrated. The news events including firm-specific and U.S. macroeconomic announcements are also addressed with descriptive statistics.

3.1 High Frequency Nordic Stock Prices

The trading data of Nordic stock prices are the tick-by-tick records of Level I order book data provided by Nasdaq Nordic. The time horizon in this research is from January 2006 to December 2009, encompassing 977 trading days. In particular, I analyze three sets of stocks separately: (i) 20 large-cap Danish companies traded on the Copenhagen exchange, (ii) 28 large-cap Swedish companies traded on the Stockholm exchange, and (iii) 29 large-cap Finnish companies traded on the Helsinki exchange. As Gençay et al. (2001) and Brownlees and Gallo (2006) discussed, several typical errors in high-frequency data are caused by humans or systems. Therefore, necessary data cleaning must be implemented before extracting the middle prices for Nordic stocks. I follow the step-by-step cleaning procedures introduced in (Barndorff-Nielsen et al., 2009, procedures P1-P3 and Q1-Q4). Additionally, I delete all observations recorded in any trading halt interval.

The data sampling from cleaned tick-by-tick data follows a two-step procedure:

1. I sample quote records every 10 seconds to generate a regular 10-second spaced data set in time from the cleaned tick data. If there is no quotation at some 10-second timestamp, I sample the nearest value for that timestamp.

2. To avoid a strong microstructure problem in jump detection, as discussed in Lee and Mykland (2008), and to reduce errors in jump detection due to the use of low-frequency data (see Christensen et al., 2014, for further details), I conservatively choose a 15-minute sample frequency from the 10-second sample[1]. The effect of microstructure noise can be found in Figure 3.2. 15-minute data provides a reliable bipower variation.

Figure 3.1 presents the histograms of the detected jumping clock times. A 1% significance level is applied to jump detection. As Figure 3.1 demonstrates, the jumps are mostly

[1]The ratios of 15-minute sample size over 10-second sample size for three Nordic markets are around 0.0111: Finland(957508/86175720), Sweden(930104/83709360) and Denmark(623360/56102400).

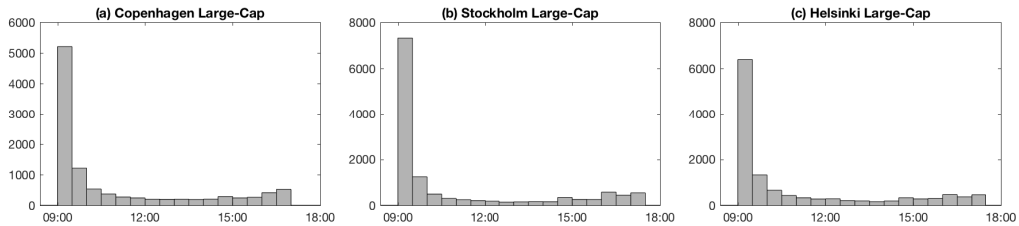

Figure 3.1: The histogram of the timestamps of detected jumps for Danish, Swedish, and Finnish large-cap stocks from 2006 to 2009. The jumps are detected using a methodology from Lee and Mykland (2008) with a sampling interval of 15 minutes with a 1% significance level, see also 2.2. The opening hours for the Copenhagen exchange are between 9:00 a.m. and 5:00 p.m. and for the Stockholm and Helsinki exchanges they are between 9:00 a.m. and 5:30 p.m.

concentrated in the first trading hour in all the markets (Copenhagen, Stockholm, and Helsinki). There is a clear morning effect, as jumps are intensively detected in the first trading hour in all markets. The morning jumps may result from the stale quotes and overnight trading. This intraday seasonal pattern is found consistently across the three Nordic exchanges.

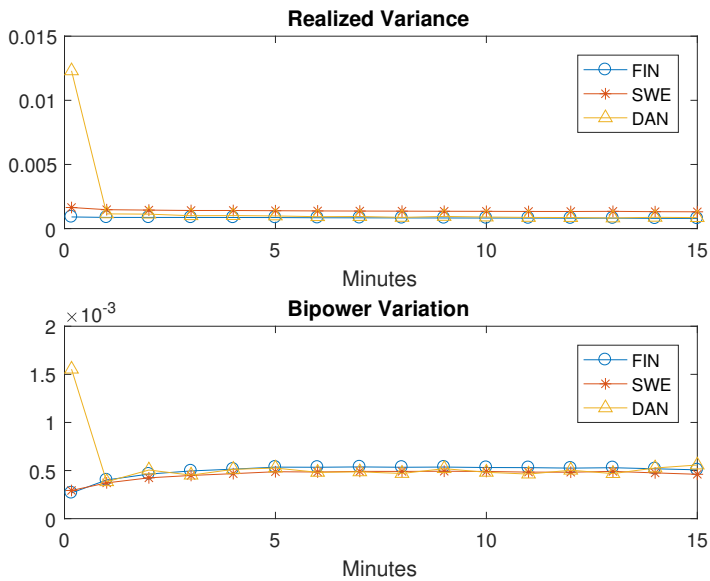

Figure 3.2: Signature plots of average realized variance and bipower variation across individual stocks in Finnish, Swedish and Danish markets. The shortest sampling interval corresponds to 10 seconds.

Figure 3.2 plots the average realized variance and bipower variation, which are calculated using 16 different sampling frequency returns: 10-second, 1-minute, 2-minute, and up to 15-minutes. The means realized variance and bipower variation are computed using prices of 27 large-cap stocks in the Finnish market, 28 large-cap stocks in the Swedish market and 20 large-cap stocks in the Danish market from 2006 to 2009. From this Figure, a strong effect of micro-structure noise on both realized variance and bipower variation can be

found using 10-second returns. However the micro-structure effect gradually disappears as the low-frequency returns are sampled. This finding is confirmed in Andersen et al. (1999) and Bandi and Russell (2008). Other research suggests using relatively high frequency stock price data. For instance, Liu et al. (2015) shows that 5-minute returns are a safe choice, and Zhang et al. (2005) argues for using all of the intraday data. Due to the illiquidity of stocks in Nordic markets, I adopted 15-minutes returns to detect jumps.

3.2 Nordic Firm Specific Announcements

Firm-specific announcements used in this research are delivered by Nasdaq Nordic continuously publishing first-hand announcements of listed companies.[2] These announcements include various types of firm-level information, such as earning announcements, news about an acquisition, takeover bid, capital increase, new product launch, expansion into new markets, signing of alliances, etc.[3] Nasdaq associates each announcement with an exact timestamp and a company name, which I then match with independent international securities identification number (ISIN) codes. For example, "Finnair sells one Embraer 170 aircraft" is announced on December 31, 2010 at 08:45 a.m. under the category "Company Announcement" and is associated with "Finnair Oyj."

To illustrate and compare the importance of schedulability of announcements on stock prices, the various announcements from Nordic Nasdaq are re-categorized into two specific groups: scheduled and non-scheduled announcements. In particular, an announcement is defined as scheduled, for example, "Interim Report", if its exact time of publication is known to the public beforehand. Generally, the date is announced in earlier stock exchange releases or on the financial calendar. Conversely, an announcement is classified as non-scheduled, for example,"Sudden Changes in Board on Management", if external stakeholders are not acknowledged in advance of the arrival time. Especially, a release is considered non-scheduled if it is irregular, its publishing schedule is not given and cannot be reliably estimated, or the release is obviously unexpected. Thus, announcements whose publishing time span is given non-specifically in earlier stock exchange releases or that is somewhat regular by nature, such as proposals by the board or nomination committee at annual general meetings, are excluded. Additionally, announcements that clearly contain no new information are excluded. In the Nordic markets, some announcements are found to be released twice in the local language and in English at slightly different clock times. In this case, only the first timestamp is applied.

Table 3.1 presents the sample sizes of scheduled and non-scheduled announcements that arrive during and after trading hours for different sets of stocks. I consider the full and two filtered sets for the announcements: the full set includes all scheduled announcements for given companies (All in the table), and filtered sets 1 and 2 exclude announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 and 48 hours on both sides, respectively. I propose to eliminate the disturbance of other announcements, often referred to as confounding events in the literature. For each company I only include announcements for which there was no other announcement in the neighborhood. Non-scheduled news is observably released primarily within non-trading hours, whereas scheduled news mostly arrives during trading hours. Furthermore,

[2] http://www.nasdaqomxnordic.com/news/companynews; see the page for detailed information.

[3] Announcements provided by Nasdaq cover the messages that were filed with Nasdaq by the respective companies. Each company may publish additional, non-regulatory news on its own website, which is not part of the data samples in this thesis.

Table 3.1: Numbers of classified company announcements in different markets between 2 January 2006 and 31 December 2009. Scheduled refers to scheduled announcements and Non-Scheduled to non-scheduled announcements. All data includes all the announcements in the sample. Filtered data set 1 excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 hours on both sides, and filtered data set 2 excludes announcements that had another announcement in the neighborhood of 48 hours on both sides.

	Scheduled announcements			**Non-scheduled announcements**		
	Trading time announcements	Non-trading time announcements	Total	Trading time announcements	Non-trading time announcements	Total
FIN						
a) All data	305	331	636	1799	749	2548
b) Filtered data set 1	152	186	338	1369	542	1911
c) Filtered data set 2	125	153	278	999	401	1400
SWE						
a) All data	198	251	449	1751	999	2750
b) Filtered data set 1	122	185	307	1295	759	2054
c) Filtered data set 2	89	142	231	810	474	1284
DAN						
a) All data	156	182	338	863	441	1304
b) Filtered data set 1	127	130	257	726	354	1080
c) Filtered data set 2	118	111	229	548	225	773

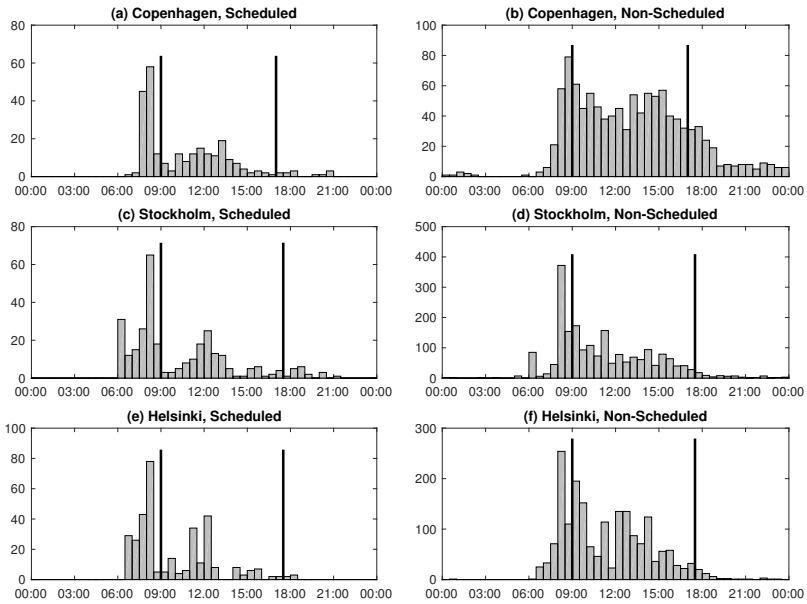

Figure 3.3: Histograms of the scheduled and non-scheduled announcements for Danish, Swedish, and Finnish large-cap companies in the samples. The vertical lines represent the opening and closing times (Copenhagen 9:00 a.m. and 5:00 p.m., Stockholm and Helsinki 9:00 a.m. and 5:30 p.m. CEST).

the histograms in Figure 3.3 show the arrival times of scheduled and non-scheduled announcements in the three markets. Here, all the announcements are included. It seems that more announcements arrive before and at opening time for both scheduled and non-scheduled announcements among the three Nordic markets. This coincides with the "morning effect" of detected jumps revealing the potential association between announcements and jumps. The sample sizes of non-scheduled announcements exceed

those of scheduled announcements. Moreover, the non-scheduled announcements are distributed more evenly than the scheduled announcements.

3.3 U.S. Macroeconomic Announcements

Table 3.2: The numbers and arrival times of U.S. macro announcements analyzed in this paper between January 2001 and December 2013.

	Trading time announcements	Non-trading time announcements	Total	Arrival time(s)
ADP Employment Change	0	89	89	8:15 AM
CPI Core Index SA	0	90	90	8:30 AM
Change in Nonfarm Payrolls	0	151	151	8:30 AM
Chicago Purchasing Manager	154	0	154	09:45 AM, 10:00 AM
FOMC Rate Decision (Upper Bound)	104	3	107	7:00 AM, 8:20 AM, 10:55 AM, 12:30 PM, 2:00 PM, 2:12 – 2:20 PM
Factory Orders	152	0	152	10:00 AM, 03:00 PM
Initial Jobless Claims	0	668	668	08:30 AM, 10:30 PM
Nonfarm Productivity	0	103	103	8:30 AM
Underemployment Rate	0	28	28	8:30 AM

Table 3.2 summarizes the macro announcement data. It is observed that there are strong overlaps in the arrivals of macro announcements[4] . The majority of selected macro announcements are released at 8:30 a.m.—an hour before the opening time of an exchange (9:30 a.m.). Additionally, one announcement type can have several announcement times. For example, Chicago Purchasing Manager, Factory Orders, and Initial Jobless Claims have two possible release times, and FOMC Rate Decision has multiple release times. Moreover, Initial Jobless Claims, Nonfarm Productivity, and Underemployment Rate are announced completely outside of trading hours.

From the detected jumps, the jump intensity of SPY is quite lower than that of equities in Nasdaq Nordic. The jump rate (the number of jumps divided by the number of trading days) for SPY is only 0.12. In contrast, the corresponding rates are between 0.18 and 0.51 across stocks on the Copenhagen exchange, between 0.22 and 1.90 across stocks on the Stockholm exchange, and between 0.14 and 0.84 across stocks on the Helsinki exchange in the samples. This might be due in part to the difference in liquidity of the markets. Another potential explanation is that the influence of announcements between Nordic firm-level news and U.S. macroeconomic news is irreversible. U.S. macro news affects Nordic markets significantly; however, Nordic firm-level news does not affect the U.S. market. More discussion on the jumps of equities and indexes can be found in Christensen et al. (2014); Lee and Mykland (2008). Moreover, jumps are found to arrive with daily seasonality: 89% of the jumps occur during the first half-hour (9:30 – 10:00 a.m.), and 92% occur during the first hour (9:30 – 10:30 a.m.).

[4] I thank Aarhus University for providing the data for macro announcements and SPY during my visiting scholar period.

4 Application of Nordic News Announcements

This chapter aims to provide a thorough discussion on the impact of the arrival of Nordic firm-specific news events on jumps in stock prices. In particular, the statistical properties of waiting times between an announcement and the first and second nearest detected jumps are examined. Additionally, jump sizes associated to firm-specific news events are discussed in details. Jumps are divided into two groups: positive and negative ones. The sizes of both positive and negative jumps associated with news events in Nordic markets statistically behave abnormally compared to their simulated reference samples. Furthermore, to illustrate the impact of individual important firm-announcements on jumps, I also tested the waiting times between the selected important announcements and the jumps to highlight the potential importance of these firm-level announcements on stock markets.

4.1 Waiting Time with the First Nearest Jump

The empirical results in this section are from Kanniainen and Yue (2017) and were obtained by Prof. Juho Kanniainen. Table 4.1 presents p-values of the two-sample, one-sided K-S test for comparing the CDFs of waiting times with real Nordic firm-specific scheduled and non-scheduled announcements and their simulated counterparts. Announcement data were collected from Nasdaq OMX Copenhagen, Stockholm, and Helsinki. Both forward and backward waiting times are considered. Additionally, I consider not only the full set of announcements but also filtered data sets 1 and 2 for eliminating the confounding effects of news events. Regarding jump detection, I apply Lee's test (Lee and Mykland, 2008) with a 1% significance level. Furthermore, the kernel smooth approach proposed by Botev et al. (2010) is applied to estimate CDFs. The reference sample size is set to be the square of the real announcement sample, as suggested by Bera et al. (2013).

In the tables, label "h_a: larger" presents an alternative hypothesis that the CDF with empirical announcements is larger than the reference CDF. Therefore, a low p-value suggests the abnormally large probability of having a jump detected after or before an announcement within a given time interval. Similarly, "h_a: smaller" labels the alternative hypothesis that the CDF with empirical announcements is smaller than the reference CDF. If these p-values are low, then the waiting times associated with the empirical announcements are larger than the reference with a great probability.

The p-values reported in Table 4.1, indicate that scheduled announcements strongly impact Nasdaq Nordic markets in terms of the jumps by the great difference between CDFs of forward waiting time for real market announcements. In particular, for the

Table 4.1: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for *Nordic* large-cap data. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	1.208E-158***	0.982	1.279E-80***	0.955	2.375E-70***	0.961
SWE	3.551E-93***	0.988	2.858E-64***	0.966	2.187E-49***	0.963
DAN	5.235E-72***	1.000	6.009E-62***	1.000	1.330E-55***	1.000
Non-Scheduled						
FIN	1.305E-21***	0.961	1.027E-06***	0.974	5.272E-05***	0.853
SWE	1.108E-04***	0.960	0.061	0.976	0.091	0.555
DAN	7.491E-16***	0.928	2.664E-12***	0.982	4.039E-10***	0.977

Panel B: Backward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.450	0.066	0.678	0.049*	0.603	0.139
SWE	0.034*	0.790	0.200	0.461	0.129	0.338
DAN	0.101	0.786	0.139	0.725	0.144	0.745
Non-Scheduled						
FIN	3.498E-03**	0.995	0.134	0.565	0.550	0.113
SWE	0.012*	0.977	0.846	0.700	0.524	0.423
DAN	0.089	0.940	0.096	0.914	0.371	0.632

Helsinki Stock Exchange, partial evidence of the statistically abnormal backward distances for the scheduled announcements is found. P-values for the alternative hypotheses "h_a: smaller" are found significant with filtered data set 1. From an economic view-point, this may signal that there is information leakage in Finnish market than the other two Nordic markets. The reason could be that investors in Finnish market might more prefer to take advantage of scheduled firm-level announcements. However, there are no consistent significance of information leakage among three datasets for each Nordic market. Similarly, the p-values related to non-scheduled announcements show that they contribute to forward jumps in the Copenhagen and Helsinki exchange data, but not in the Stockholm exchange, due to insignificant K-S tests.

The median and mean tests for the forward and backward waiting times are also presented for comparing waiting times between the empirical and simulated samples. Table 4.2 shows the left- and right-tailed p-values using bootstrapping and the Welch U-test method against the reference data samples. Bootstrapping is based on 10,000 iterations, and thus, the medians and means of the reference samples are based on the pooled data over all 10,000 subsamples. These tables report the results only for filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides. In Table 4.2, the null hypothesis is rejected with both bootstrapping and the Welch U-test for the Copenhagen exchange data, but not for the Stockholm exchange data, which is consistent with the K-S test results. However, inconsistencies

Table 4.2: Medians and means of the forward and backward distances for the Nasdaq Nordic data sample. The results are based on filtered data set 1 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 hours on both sides. The Bootstr. p left tail and Bootstr. p right tail are the left- and right-tailed p-values calculated with the bootstrapping method, respectively, and the Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A: Forward Distances

	Median of d^-	Median of $\tilde{d}^-$	Bootstr. p left tail	Bootstr. p right tail	Mean of d^-	Mean of $\tilde{d}^-$	Bootstr. p left tail	Welch U-test p left tail	Bootstr. p right tail	Welch U-test p right tail
Scheduled										
FIN	0.253	26.503	0***	1.000	19.795	38.883	0***	2.526E-38***	1.000	1.000
SWE	0.253	23.230	0***	1.000	19.410	34.866	0***	3.347E-30***	1.000	1.000
DAN	0.253	19.530	0***	1.000	12.535	29.293	0***	5.658E-33***	1.000	1.000
Non-Scheduled										
FIN	25.253	26.500	0.039*	0.961	38.368	39.870	0.062	2.809E-03**	0.938	0.997
SWE	24.023	24.224	0.332	0.668	34.627	35.565	0.134	0.080	0.866	0.920
DAN	15.499	18.928	0***	1.000	25.258	28.245	0***	2.605E-09***	1.000	1.000

Panel B: Backward Distances

	Median of d^-	Median of $\tilde{d}^-$	Bootstr. p left tail	Bootstr. p right tail	Mean of d^-	Mean of $\tilde{d}^-$	Bootstr. p left tail	Welch U-test p left tail	Bootstr. p right tail	Welch U-test p right tail
Scheduled										
FIN	27.997	27.958	0.528	0.472	46.852	41.916	0.984	0.867	0.016*	0.133
SWE	25.997	25.997	0.779	0.221	36.951	38.296	0.276	0.341	0.724	0.659
DAN	19.221	23.099	0.076	0.924	30.108	31.701	0.201	0.047*	0.800	0.953
Non-Scheduled										
FIN	26.748	26.999	0.340	0.660	40.030	41.420	0.076	0.370	0.924	0.630
SWE	25.997	25.997	0.944	0.056	37.748	37.664	0.534	0.533	0.466	0.467
DAN	20.281	22.086	0.032*	0.968	29.711	30.604	0.153	0.056	0.847	0.944

are found between Tables 4.1 and 4.2 with non-scheduled announcements on the Helsinki exchange, as the medians and means of forward waiting times are not always statistically significantly different. In this case, I prefer the results of the K-S test, as it is a global, non-parametric test over the entire domain.

Furthermore, filtering out confounding events is strongly suggested before analyzing the data. Table 4.1 demonstrates clearly the abnormal behavior of the backward differences between Swedish and Finnish markets when all the data are used; however, after the cases with neighborhood events are filtered, no clear evidence of information leakage can be provided.

4.2 Waiting Times with the Second Nearest Jumps

This section is aimed at providing an alternative examination of the impacts of scheduled and non-scheduled announcements on Nordic stock prices. Instead of focusing on the waiting times between given announcements and the nearest backward and forward detected jumps, the waiting times for the second nearest jumps are considered. The reason why it is necessary to robustly check the influence of announcements on jumps is that there might be a continuous effect of the arriving news. The expectations of investors regarding the same announcements are different not only in direction but also in persistence. Therefore, the market might react to announcements in terms of multiple sequential jumps.

Figure 4.1 demonstrates the CDF of real announcements and reference CDF of waiting times between scheduled announcements and the second nearest detected jumps for the Finnish, Swedish, and Danish markets. The Figure does not plot the whole distribution curves. This is because the statistical behavior of small waiting times is stressed and locally zoomed in. The smaller the waiting time, the faster the market react to announcements in term of jumps. It is observed that for forward distances the CDFs of real announcements are higher than their reference counterparts among the three markets. This finding is also statistically confirmed from the strong significant p-values in the K-S test in Table 4.3 and Welch U-test in Table 4.4. However, the backward CDFs are not observed to be different. The p-values of the K-S test show that the backward CDFs of real scheduled announcements are significantly lower than their reference CDFs only in the Finnish market. This is confirmed by the Welch U-test. No significant evidence is found from the Swedish and Danish samples.

Regarding non-scheduled announcements, both forward and backward CDFs of real announcements are statistically lower than their reference CDFs in the three Nordic markets. The means of empirical forward and, in particular, backward waiting times are larger than that of the reference sample. Almost all these findings are consistent among the three data sets, except tests on non-scheduled announcements in the Danish market. The results for backward waiting times of non-scheduled announcements suggest that information leakage might exist in Nordic markets, as there are jumps observed in advance of real announcements, but not for the general reference events. This means that the market significantly reacts to forthcoming non-scheduled firm-level information.

If the impact of scheduled and non-scheduled announcements on Nordic stock prices are in terms of not only the first nearest but also the second nearest jumps, one natural question is whether these two (pre-)sequential jumps arrive at the same speed for real announcements and reference announcements. Intuitively, the first jumps should reflect

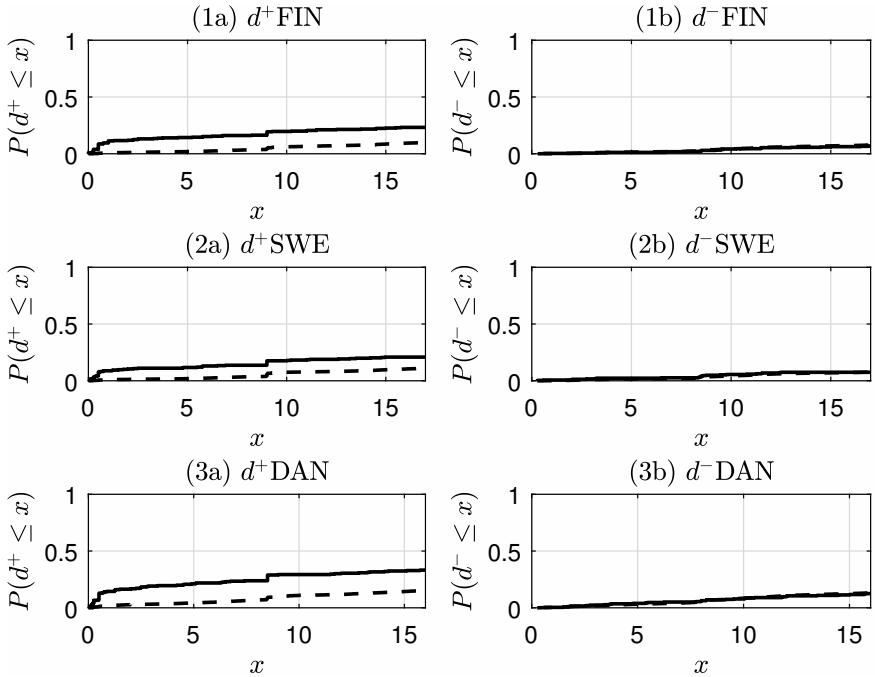

Figure 4.1: CDFs of the distances between *scheduled* announcements and the second nearest jumps for Nordic large-cap companies based on filtered data set 1 (excluding announcements that had another announcement in the neighborhood of 6 hours on both sides). d^+ refers to forward distances and d^- to backward distances. Distances are expressed in hours. The solid line plots the CDF based on the actual timestamps (real announcements), and the dashed line represents the reference CDF based on the reference data set.

information more actively than the second ones given sufficient market efficiency, because the first jump tends to contain more information regarding the coming announcement.

For the sake of robustness, it is helpful to investigate the distances between the first and second nearest jumps. The corresponding test results are reported in Table 4.5 and 4.6. For forward distances, as shown in Panel A of Table 4.6, the means of incremental waiting time for real scheduled and non-scheduled announcements are consistently larger than their reference counterparts. Since the means of empirical waiting times with first and second jumps are both smaller than the reference means, we might conclude generally that the second jumps indeed occur relatively slower than the first jumps in the sense of comparing the speed with their reference waiting times. This can also be seen by directly comparing the difference between the means of empirical waiting times and reference waiting times for the first and second jumps, respectively. For instance, if we consider scheduled announcements in the Finnish market, then the mean difference of forward waiting times for first jumps is around 19 hours, which is much larger than that of waiting times for second jumps (around 7 hours; see Table 4.4). This observation implies that the information of scheduled announcements is mostly absorbed into the first nearest jumps, since the difference between the statistical property of real and reference waiting times of first jumps is much more larger than the second one. Similarly, the same conclusion is obtained for backward scheduled announcements that the pre-announcement first jump contains more information from the forthcoming announcement than the second jump

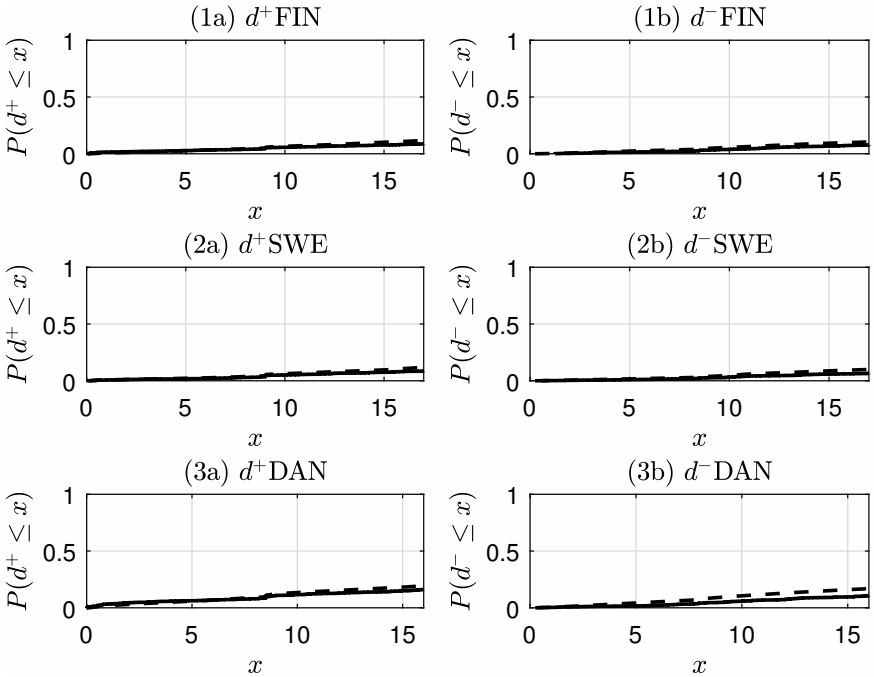

Figure 4.2: CDFs of the distances between *non-scheduled* announcements and the second nearest jumps for Nordic large-cap companies based on filtered data set 1 (excluding announcements that had another announcement in the neighborhood of 6 hours on both sides). d^+ refers to forward distances and d^- to backward distances. Distances are expressed in hours. The solid line plots the CDF based on the actual timestamps (real announcements), and the dashed line represents the reference CDF based on the reference data set.

does in terms of relative reaction speed to the reference announcements. However, there is no such observation for backward non-scheduled announcements. This is due to the difficulty of making a prediction on the basis of forthcoming non-scheduled news.

The main findings in this section are as follows: first, jumps are strongly associated with scheduled announcements. Second, scheduled and non-scheduled announcements have continual impacts on Nordic markets in terms of (pre-)sequential jumps. Third, the reactions of the second jumps to announcements are weaker than the first jumps. In other words, the second jumps contain less information than the first ones.

Table 4.3: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Nordic large-cap data with the second detected nearest jump. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of empirical announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances

	a) All Data		**b) Filtered Data Set 1**		**c) Filtered Data Set 2**	
	h_a**: larger**	h_a**: smaller**	h_a**: larger**	h_a**: smaller**	h_a**: larger**	h_a**: smaller**
Scheduled						
FIN	1.507E-13***	0.52	8.547E-07***	0.81	2.476E-05***	0.79
SWE	4.274E-08***	0.36	4.143E-04***	0.93	7.296E-05***	0.96
DK	7.351E-11***	0.99	2.268E-09***	0.99	1.212E-09***	0.99
Non-Scheduled						
FIN	0.26	3.012E-09***	0.74	1.254E-06***	0.81	3.152E-05***
SWE	0.94	7.650E-28***	0.99	4.051E-15***	0.81	9.793E-04***
DK	0.41	2.221E-06***	0.61	4.049E-03**	0.49	0.52

Panel B: Backward Distances

	a) All Data		**b) Filtered Data Set 1**		**c) Filtered Data Set 2**	
	h_a**: larger**	h_a**: smaller**	h_a**: larger**	h_a**: smaller**	h_a**: larger**	h_a**: smaller**
Scheduled						
FIN	0.97	6.095E-04***	0.99	3.542E-03**	0.86	4.967E-03**
SWE	0.77	0.20	0.88	0.20	0.84	0.22
DK	0.77	0.16	0.78	0.21	0.45	0.47
Non-Scheduled						
FIN	0.99	3.812E-06***	0.99	6.097E-03**	1.000	1.618E-05***
SWE	0.99	4.848E-31***	0.99	7.509E-18***	0.99	1.797E-06***
DK	0.99	1.040E-12***	0.99	9.311E-06***	0.99	5.870E-03**

Table 4.4: Means of waiting times with the second detected jump for Nordic large-cap data. The results are based on all announcements and the filtered data set 1 and 2 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data).

Panel A Forward Distances	**#Obs of d^{2nd}**	**Mean of d^{2nd}**	**#Obs of $\tilde{d}^{2nd}$**	**Mean of $\tilde{d}^{2nd}$**	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	630	68.33	243795	75.22	4.194E-06***	1.000
SWE	449	62.67	149810	66.61	2.075E-03**	0.99
DK	337	45.20	101477	57.74	1.543E-08***	1.000
Non-Scheduled						
FIN	2514	76.75	2574023	68.11	1.000	9.125E-13***
SWE	2725	71.56	2731135	61.13	1.000	5.763E-32***
DK	1296	54.73	1193343	49.72	1.000	4.826E-07***
b) Filtered Data Set 1						
Scheduled						
FIN	336	67.78	85738	76.03	1.577E-04***	0.99
SWE	307	63.19	77189	68.05	8.189E-03**	0.99
DK	256	44.84	58514	57.26	6.473E-07***	1.000
Non-Scheduled						
FIN	1887	77.46	1686896	69.96	1.000	1.837E-08***
SWE	2034	73.13	1673992	64.07	1.000	5.513E-17***
DK	1074	55.46	858607	52.25	0.99	1.805E-03**
c) Filtered Data Set 2						
Scheduled						
FIN	243	69.64	50811	77.00	2.355E-03**	0.99
SWE	200	59.91	33176	68.62	1.349E-03**	0.99
DK	215	44.49	41523	59.14	4.837E-07***	1.000
Non-Scheduled						
FIN	1075	77.62	635465	70.44	1.000	8.833E-07***
SWE	851	74.38	391443	67.38	0.99	1.398E-04***
DK	590	55.72	305135	54.47	0.72	0.27

Panel B Backward Distances	**#Obs of d^{2nd}**	**Mean of d^{2nd}**	**#Obs of $\tilde{d}^{2nd}$**	**Mean of $\tilde{d}^{2nd}$**	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	630	84.71	243795	77.56	0.99	1.254E-03**
SWE	449	72.39	149810	69.68	0.72	0.27
DK	337	61.73	101477	60.10	0.73	0.26
Non-Scheduled						
FIN	2514	74.94	2574023	69.20	1.000	3.737E-08***
SWE	2725	73.90	2731135	62.29	1.000	6.769E-40***
DK	1296	58.85	1193343	51.96	1.000	1.150E-15***
b) Filtered Data Set 1						
Scheduled						
FIN	336	90.57	85738	78.79	0.99	9.106E-04***
SWE	307	75.61	77189	71.79	0.89	0.10
DK	256	61.46	58514	59.40	0.68	0.31
Non-Scheduled						
FIN	1887	76.28	1686896	71.06	0.99	1.031E-04***
SWE	2034	74.98	1673992	65.30	1.000	5.545E-24***
DK	1074	59.19	858607	54.40	1.000	1.058E-06***
c) Filtered Data Set 2						
Scheduled						
FIN	243	92.39	50811	80.09	0.99	6.821E-03**
SWE	200	73.96	33176	72.09	0.80	0.19
DK	215	62.20	41523	61.46	0.52	0.47
Non-Scheduled						
FIN	1075	80.34	635465	71.78	1.000	2.944E-08***
SWE	851	77.41	391443	68.80	1.000	7.928E-07***
DK	590	62.13	305135	56.80	0.99	1.490E-03**

Table 4.5: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Nordic large-cap data with the Waiting Time between the First and the Second Nearest Jump. Testing whether the empirical and randomly generated waiting times between the first and the second nearest jump come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the waiting time differences with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of empirical announcements. Panels A and B report the forward difference and the backward difference. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances between the Nearest First and Second Jumps

	a) All Data		**b) Filtered Data Set 1**		**c) Filtered Data Set 2**	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	2.699E-02*	1.134E-08***	9.753E-02	3.426E-04***	0.12	2.344E-03**
SWE	7.425E-03**	4.999E-06***	0.12	2.313E-04***	5.373E-02	5.738E-02
DK	4.511E-02*	2.665E-03**	2.258E-02*	2.586E-02*	5.174E-02	7.760E-02
Non-Scheduled						
FIN	0.74	1.887E-16***	0.94	1.527E-05***	0.99	2.235E-06***
SWE	0.99	7.908E-24***	0.99	1.413E-12***	0.99	5.587E-04***
DK	0.95	1.018E-13***	0.99	1.537E-07***	0.93	9.733E-03**

Panel B: Backward Distances between the Nearest First and Second Jumps

	a) All Data		**b) Filtered Data Set 1**		**c) Filtered Data Set 2**	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.82	0.28	0.94	5.822E-02	0.93	6.193E-02
SWE	0.62	0.11	0.98	0.14	0.98	0.13
DK	0.90	0.11	0.96	0.12	0.89	0.15
Non-Scheduled						
FIN	0.99	4.709E-04***	0.92	0.11	0.99	1.108E-02*
SWE	0.96	6.427E-28***	0.84	9.818E-15***	0.99	1.118E-04***
DK	0.99	2.959E-16***	1.000	2.951E-08***	1.000	1.511E-03**

Table 4.6: Means of waiting times between the detected first and second jump for Nordic large-cap data. The results are based on all announcements and the filtered data set 1 and 2 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data).

Panel A	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test p left tail**	**Welch U-test**
Forward Distances	**Δd**	**Δd**	**$\Delta\tilde{d}$**	**$\Delta\tilde{d}$**	**p left tail**	**p right tail**
a) All Data						
Scheduled						
FIN	630	47.78	103246	38.03	0.99	7.964E-04***
SWE	449	43.58	76333	34.62	0.99	9.154E-03**
DK	337	32.86	56494	29.07	0.57	0.42
Non-Scheduled						
FIN	2514	39.91	730477	34.10	1.000	9.445E-18***
SWE	2725	38.07	1042157	31.43	1.000	6.071E-21***
DK	1296	29.71	418948	24.88	1.000	4.887E-16***
b) Filtered Data Set 1						
Scheduled						
FIN	336	48.17	46548	38.77	0.96	3.181E-02*
SWE	307	43.78	40853	35.22	0.98	1.084E-02*
DK	256	32.25	36661	28.57	0.46	0.53
Non-Scheduled						
FIN	1887	39.15	518195	35.08	1.000	1.276E-07***
SWE	2034	38.80	694026	32.98	1.000	9.905E-11***
DK	1074	30.20	315253	26.33	1.000	8.514E-10***
c) Filtered Data Set 2						
Scheduled						
FIN	243	48.52	28569	39.34	0.94	5.475E-02
SWE	200	39.90	20668	35.73	0.69	0.30
DK	215	3182	26488	2935	0.32	0.67
Non-Scheduled						
FIN	1075	39.23	229339	35.30	1.000	1.683E-07***
SWE	851	39.77	190812	34.51	0.99	8.406E-05***
DK	590	29.28	129204	27.45	0.99	6.486E-03**

Panel B	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test**	**Welch U-test**
Backward Distances	**Δd**	**Δd**	**$\Delta\tilde{d}$**	**$\Delta\tilde{d}$**	**p left tail**	**p right tail**
a) All Data						
Scheduled						
FIN	630	39.65	103246	38.22	0.91	8.280E-02
SWE	449	37.01	76333	34.20	0.95	4.658E-02*
DK	337	31.86	56494	29.12	0.95	4.683E-02*
Non-Scheduled						
FIN	2514	36.44	730477	34.10	0.99	7.656E-05***
SWE	2725	37.42	1042157	31.30	1.000	2.146E-27***
DK	1296	29.22	418948	24.83	1.000	3.417E-13***
b) Filtered Data Set 1						
Scheduled						
FIN	336	43.71	46548	38.54	0.99	2.554E-03**
SWE	307	38.66	40853	35.19	0.94	5.320E-02
DK	256	31.39	36661	28.73	0.94	5.424E-02
Non-Scheduled						
FIN	1887	36.22	518195	34.91	0.93	6.839E-02
SWE	2034	37.39	694026	32.80	1.000	8.390E-13***
DK	1074	29.49	315253	26.18	1.000	7.212E-07***
c) Filtered Data Set 2						
Scheduled						
FIN	243	44.19	28569	39.21	0.99	8.857E-03**
SWE	200	39.77	20668	35.25	0.93	6.286E-02
DK	215	31.74	26488	29.50	0.89	0.10
Non-Scheduled						
FIN	1075	38.27	229339	35.31	0.99	2.856E-03**
SWE	851	38.99	190812	34.41	0.99	9.939E-05***
DK	590	31.16	129204	27.60	0.99	6.853E-04***

4.3 Analysis of the Sizes of Jumps Related to News Events

4.3.1 Introduction

This section discusses the statistical characteristics of jump sizes for stock prices associated with scheduled and non-scheduled announcements in the Helsinki, Stockholm, and Copenhagen exchanges. All jump sizes are the absolute value of detected extremal log returns divided by the corresponding volatility—that is, the statistics $\mathcal{L}$ in Eq. 2.2. The simultaneous volatility is estimated by bipower variation. The advantage of considering normalized jumps rather than pure jumps is that the statistics $\mathcal{L}$, like the Sharpe Ratio, contains information on volatility risk. In addition to studying the sizes of all detected jumps, the detected jumps are classified into two groups with different signs, and the announcement-associated positive and negative jump sizes are examined separately by comparing the distribution functions and means between empirical and simulated reference samples.

Jumps in asset prices are well-documented in the finance literature; see Bates (1996) and Lee and Mykland (2008). The size of a jump, as a measure of abrupt discontinuity in asset prices, is an essential financial variable for both asset pricing (Bates (2000); Kou and Wang (2004); Merton (1976)) and risk management (Bollerslev et al. (2008); Yan (2011)). On the one hand, jump sizes precisely describe the reaction of stock markets to some potential innovations; on the other hand, the sizes of jumps and their distributions provide investors with deep insights into the movement of stock prices. What is more important is to have a profound understanding of jump sizes and their relationship to the arrival of announcements. This is especially meaningful for investors. Digesting this public information and grasping the potential relationship between announcements and jumps are two tools for managing or even predicting jumps in their assets. However, most literature on jumps only provides an overview of the statistical properties of sizes and signs of jumps without a classification according to different news impacts. There have only been limited analyses relating jumps directly to news. Lahaye et al. (2011) provided three sources of jumps associated with news: (1) selected important news, (2) foreign news and news out of list, and (3) idiosyncratic liquidity shocks from traders moving into and out of markets. Additionally, the author provided empirical evidence that co-jumps are generated mainly by macroeconomic announcements. Lee (2012) also found that jump arrivals are predictable and normally distributed after macroeconomic information releases. Miao et al. (2014) examined the association between macroeconomic news arrivals with S&P500 futures. They documented that most jumps are detected in the first five minutes of a trading day. Boudt and Petitjean (2014) investigated liquidity and news releases around jumps based on stocks in the Dow Jones Industrial Average Index. One interesting finding is that the number of trades is a key driver of jumps. Bradley et al. (2014) studied the effect of an analyst's recommendation and found that markets react to these recommendations significantly in terms of jumps. An analyst's advice is still the most important information source for investors, even though the distribution timing is delayed by 30 minutes on average.

It is noted that most research on the relationship between jump sizes and news arrivals are in a simply qualitative manner. Jumps are concluded to be associated to certain news if their timestamps are relatively close; see Lee and Mykland (2008), Lahaye et al. (2011) and Miao et al. (2014). This treatment is straightforward; nevertheless, it ignores the various impacts of different types of announcements. Furthermore, the contribution and statistical property of some class of news to (positive and negative) jump sizes will be

covered up. Working in the statistical framework for waiting times allows for classifying jumps and their sizes according to the arrivals of certain announcements, sufficiently considering the timeliness of news and related jumps. As a result, how (positive and negative) jump sizes are associated with scheduled and non-scheduled announcements can be clearly answered. What is more, the sample of detected jumps associated with announcements conveys more accurate information to investors, since waiting time is a proper measure of the market reaction to the arrival of news.

Given empirical and simulated scheduled and non-scheduled announcements, the nearest forward and backward jumps (positive and negative jumps) are collected for measuring their sizes. Then K-S and Welch U-test are applied to empirical jump sizes and their reference counterparts. The empirical analysis shows that large jumps significantly follow scheduled announcements. In contrast, backward non-scheduled announcements do not contribute to jumps in abnormal sizes. Additionally, negative jumps are found to dominate positive jumps in number and size for both scheduled and non-scheduled announcements.

4.3.2 Empirical Results

In the procedure for specifying the waiting times between news arrivals and the first detected jumps, I record all detected jumps (extremal log returns), which are normalized by volatility. The sizes of these normalized jumps are associated with scheduled and non-scheduled announcements on both forward and backward directions. I also consider the characteristics of distributions for the sizes of detected jumps—positive and negative jumps, respectively.

Analysis of All Jump Sizes

Table 4.7 reports the test results on the consistency of distribution functions for the sizes of normalized jumps between the empirical distribution and their reference counterparts in the Nordic market samples. I focus on the jumps associated with both scheduled and non-scheduled announcements related to large-cap companies in Nordic markets.

For the normalized jump sizes that are associated with scheduled announcements and specified with forward distances, statistically the empirical distribution function is smaller than the reference one consistently among both filtered and non-filtered data sets. Scheduled announcements tend to be followed by larger jumps compared to general reference announcements. The arrival of a scheduled announcement significantly enlarges the probability of markets generating a large jump, which sufficiently improves the efficiency of the markets. This means that scheduled announcements are effective and valuable information to most investors.

Regarding the forward normalized jump sizes associated with non-scheduled announcements, the empirical distribution function is tested and shown to be smaller than the reference distribution function. However, this finding is weakly consistent among filtered data sets. For filtered data set 1 consisting of the announcements uniquely arriving in the neighborhood of 6 hours on both sides, the Swedish market shows no significance. For filtered data set 2, which excludes announcements with another announcement in the same neighborhood of 48 hours on both sides, the Finnish and Swedish markets are not significant. Compared with forward scheduled announcements, the weaker evidence from non-scheduled announcements reveals weak predictability for future jumps given a non-scheduled news event. If investors gain no information (arrival time and content) about the announcements in advance, the null hypothesis will be accepted. There is

almost no difference among the markets in the generation of jumps, based on randomly selected reference timings and real announcements. Additionally, the different test results from data sets with and without filters illustrate the necessity of excluding redundant arrivals for one type of announcement in a neighbor period.

For the normalized jump sizes, which are associated with scheduled announcements and specified with backward distance, we can hardly conclude that the empirical distribution function is higher than reference one in the Finnish and Danish markets. There is insufficient evidence to reject that the empirical distribution function of jump sizes is different from the reference one based on data sampling from the Swedish market. These findings are consistent among filtered data sets 1 and 2. The tests indicate that before the arrival of scheduled announcements, the markets in Finland and Denmark are even more peaceful than in general moments in terms of jumps; however, no such statistical evidence exists in relation to the market in Sweden. This may statistically deny the fact that investors trade scheduled announcements beforehand.

However, the backward normalized jump sizes associated with non-scheduled announcements tell us very little. There is fairly weak evidence that the empirical distribution function is higher than reference distribution for the Swedish market. There is insufficient evidence to reject that the empirical distribution function of jump sizes is different from the reference one based on the data sets sampled from the Finnish and Danish markets. The tests present that before the arrivals of non-scheduled announcements, the market in Stockholm is even less active than in general moments in terms of jumps. Nevertheless, no similar significant statistical conclusions can be made about Helsinki and Copenhagen.

Table 4.8 presents the mean test results for the sizes of normalized jumps for Nordic markets. We can observe that the mean values of empirical forward jump sizes associated with scheduled announcements are statistically larger than the means of reference samples consistently among the filtered data sets. Similarly, the mean values of empirical jump sizes associated with non-scheduled announcements are statistically larger than the means of the reference data, although this empirical property is not consistent among all data sets. For filtered data sets 1 and 2, the Swedish market has no significance.

Concerning backward normalized jump sizes, weak evidence is found for scheduled announcements that the mean values of the empirical sample are statistically smaller than the means of reference samples in the Finnish and Danish markets. The Welch U-test does not enable us to statistically reject that the mean of the empirical jump sizes is different from the reference one based on data sampling from the Swedish market. These test results are consistent among all filtered and non-filtered data sets. However, few statistically significant p-values for non-scheduled announcements are observed. The mean value of empirical jump sizes associated with scheduled announcements is statistically smaller than the mean of Swedish reference samples from only filtered samples 1 and 2. The equality of the means of empirical jump sizes and their counterparts from the reference data is not rejected for the Finnish and Danish markets. The Welch U mean tests strongly support our findings from the K-S tests, especially for jumps related to forward waiting times. For scheduled announcements, the p-values of these two tests present consistent significance. Even though some weak results are found for non-scheduled announcements, the two tests still indicate the same fact, for example, in the Swedish market. The above consistent empirical findings show that the sizes of extrenal returns (jumps) vary according to the arrival of announcements, particularly in the case of scheduled announcements. From the reaction of asset prices, the schedulability of announcements is an important factor for

Table 4.7: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Nordic large-cap data of Normalized Jump Sizes Testing whether the empirical and randomly selected jump sizes come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the jump sizes with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the normalized jumps associated to forward distances and the backward distances. The results are based on all announcements, filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Sizes of Forward Normalized Jumps

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.99	2.653E-41***	1.000	2.794E-24***	0.99	2.585E-17***
SWE	0.98	6.745E-27***	0.97	3.737E-20***	0.88	5.916E-15***
DK	0.94	1.571E-12***	0.99	1.497E-14***	0.98	1.662E-12***
Non-Scheduled						
FIN	0.97	4.274E-07***	0.99	1.475E-02*	0.97	0.18
SWE	0.97	5.296E-03**	0.35	0.72	0.21	0.88
DK	0.91	4.663E-05***	0.87	1.899E-04***	0.81	2.557E-02*

Panel B: Sizes of Backward Normalized Jumps

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	5.831E-02	0.94	1.765E-02*	0.99	2.367E-02*	0.99
SWE	0.72	0.35	0.98	0.41	0.68	0.51
DK	1.136E-02*	0.95	1.504E-02*	0.97	1.893E-02*	0.97
Non-Scheduled						
FIN	0.96	0.1.754E-02*	0.82	0.44	0.74	0.47
SWE	5.421E-03**	0.72	1.092E-02*	0.88	6.148E-02	0.96
DK	7.343E-02	0.43	0.36	0.22	0.35	0.33

investors to evaluate the coming news and make trading decisions.

Table 4.8: Means of normalized jump sizes for Nordic large-cap data. The results are based on all announcements and the filtered data set 1 and 2 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	636	15.30	404325	10.44	1.000	2.158E-39***
SWE	448	15.56	201470	12.09	1.000	3.080E-28***
DK	337	13.57	113906	10.79	1.000	5.341E-10***
Non-Scheduled						
FIN	2548	11.89	6489006	10.36	1.000	1.388E-07***
SWE	2747	12.63	7555080	11.59	0.98	1.226E-02*
DK	1302	15.20	1695248	10.86	0.99	1.919E-04***
b) Filtered Data Set 1						
Scheduled						
FIN	338	15.52	114189	10.41	1.000	5.494E-25***
SWE	307	16.37	94183	11.59	1.000	1.557E-20***
DK	256	14.44	65854	10.89	1.000	3.387E-12***
Non-Scheduled						
FIN	1911	11.13	3650026	10.37	0.99	1.603E-03**
SWE	2053	12.87	4214741	11.75	0.42	0.57
DK	1078	12.78	1163218	10.86	0.99	4.711E-04***
c) Filtered Data Set 2						
Scheduled						
FIN	278	15.12	77259	10.32	1.000	2.965E-18***
SWE	231	14.00	53328	11.96	1.000	3.098E-14***
DK	228	14.15	52285	10.94	1.000	1.378E-09***
Non-Scheduled						
FIN	1400	10.64	1958853	10.38	0.91	8.723E-02
SWE	1283	12.75	1647343	11.91	0.15	0.84
DK	773	12.06	596044	10.78	0.96	3.365E-02*

Panel B **Backward Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	636	10.36	404325	10.51	2.326E-02*	0.97
SWE	448	10.16	201470	11.46	0.65	0.34
DK	337	9.0.18	113906	10.44	1.596E-03**	99
Non-Scheduled						
FIN	2548	11.22	6489006	10.50	0.96	3.430E-02*
SWE	2747	11.24	7555080	11.15	0.10	0.89
DK	1302	11.52	1695248	10.53	0.19	0.80
b) Filtered Data Set 1						
Scheduled						
FIN	338	10.32	114189	10.58	6.673E-03**	0.99
SWE	307	10.37	94183	11.29	0.75	0.24
DK	256	8.958	65854	10.53	1.038E-03**	0.99
Non-Scheduled						
FIN	1911	11.25	3650026	10.51	0.75	0.24
SWE	2053	11.40	4214741	11.29	5.388E-02*	0.94
DK	1078	11.82	1163218	10.51	0.38	0.61
c) Filtered Data Set 2						
Scheduled						
FIN	278	9.221	77259	10.49	1.240E-02*	0.98
SWE	231	9.930	53328	11.07	0.51	0.48
DK	228	8.969	52285	10.72	1.541E-03**	0.99
Non-Scheduled						
FIN	1400	10.67	1958853	10.46	0.64	0.35
SWE	1283	12.00	1647343	11.40	2.209E-02*	0.97
DK	773	11.57	596044	10.46	0.35	0.64

Analysis of Positive Jump Sizes

Table 4.9 reports the results regarding the identity of distribution functions for the sizes of positive normalized jumps between empirical scheduled and non-scheduled announcements and their counterparts in the Nordic markets. All negative jumps are excluded from the samples used in this analysis.

For positive jump sizes, which are associated with scheduled announcements and specified with forward distances, there is strong statistical evidence that the CDF of empirical jump sizes is smaller than the reference one consistently among both filtered and non-filtered data sets. Scheduled announcements tend to be followed by larger positive jumps compared to general reference announcements. The arrivals of scheduled announcements significantly activate markets in terms of large positive jumps, thereby sufficiently contributing to the efficiency of markets.

Regarding the forward normalized jump sizes associated with non-scheduled announcements, p-values show that the CDF of empirical jump sizes is lower than the reference distribution function only in Finnish and Danish markets with non-filtered data. However, this finding is not reliable and robust, as no significance is found when filtered data set 2 is applied. Compared with forward scheduled announcements, the weaker evidence from non-scheduled announcements reveals weak predictability for future positive jumps given a non-scheduled news event. This supports the corresponding results when all jump sizes are investigated. If the null hypothesis is not rejected, there will be almost no difference in the distributions of empirical and reference samples.

For the normalized positive jump sizes, which are associated with scheduled announcements and specified with backward distance, weak evidence is found that the empirical distribution function is higher the than reference one in Finland and Denmark . There is insufficient evidence to reject that the empirical distribution function of jump sizes is different from the reference one based on data sampling from the Swedish market. These findings are not consistent among all data sets. As the tests indicate, we cannot conclude that the empirical distribution of positive jump sizes is different from the reference distribution function in a statistically robust way.

Conversely, from the backward normalized jump sizes associated with non-scheduled announcements in the Swedish market, I observe consistently that the CDF of empirical jump sizes is higher than the reference distribution. There is insufficient robust evidence to reject that the empirical distribution function of positive jump sizes is different from the reference one based on the data sets for the Finnish and Danish markets. The tests present that before the arrival of non-scheduled announcements, the market in Stockholm is even less active than in general moments in terms of jumps. However, there are no similar significant statistical conclusions in the cases of Helsinki and Copenhagen.

Table 4.10 demonstrates the mean test results for normalized positive jump sizes in the Nordic markets. We can observe that the mean values of empirical forward positive jump sizes associated with scheduled announcements are statistically larger than the means of the reference samples consistently among the filtered data sets. The mean values of empirical positive jump sizes associated with non-scheduled announcements are also statistically larger than the means of the reference data. This empirical property is not consistent among all data sets. For filtered data sets 1 and 2, the Swedish market has no significance.

Regarding backward normalized jump sizes, weak evidence is found for scheduled an-

Table 4.9: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Nordic large-cap data of Positive Normalized Jumps. Testing whether the empirical and randomly selected positive normalized jumps come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the jumps with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the positive normalized jumps associated to forward distances and the backward distances. The results are based on all announcements, filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Sizes of Forward Positive Normalized Jumps

	a) All Data		b) Filtered Data Set 1.		c) Filtered Data Set 2.	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.99	7.218E-17***	0.99	5.094E-11***	0.97	1.434E-08***
SWE	0.97	5.185E-14***	0.93	2.734E-13***	0.86	1.408E-09***
DK	0.80	4.211E-09***	0.95	3.887E-11***	0.87	9.908E-10***
Non-Scheduled						
FIN	0.78	3.207E-03**	0.94	0.11	0.83	0.32
SWE	0.67	0.14	3.943E-02*	0.72	0.17	0.87
DK	0.82	2.023E-02*	0.86	2.939E-02*	0.84	0.53

Panel B: Sizes of Backward Positive Normalized Jumps

	a) All Data		b) Filtered Data Set 1.		c) Filtered Data Set 2.	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.29	0.41	8.736E-02*	0.98	0.20	0.93
SWE	0.84	0.42	0.96	0.34	0.80	0.29
DK	9.277E-03**	0.94	0.12	0.97	8.546E-02*	0.97
Non-Scheduled						
FIN	0.77	4.727E-02*	0.59	0.56	0.39	0.76
SWE	1.369E-02*	0.52	1.710E-02*	0.75	8.763E-03**	0.99
DK	3.182E-02*	0.71	0.17	0.65	0.17	0.56

nouncements that the mean values of the empirical sample are statistically smaller than those of the reference samples only in Denmark. The results of the Welch U-test do not allow us to confidently reject that the mean of empirical jump sizes is different from the reference one based on data sampling from the Finnish and Swedish markets. These test results are consistent among all filtered and non-filtered data sets. However, few statistically significant p-values for non-scheduled announcements are observed. The mean values of empirical jump sizes associated with scheduled announcements are statistically smaller than the mean of reference samples for Sweden from all datasets. The equality of means between empirical positive jump sizes and its counterpart from the reference data for Finnish and Danish markets is not rejected.

The Welch U mean test results are strongly consistent with our findings from the K-S tests, in particular for jumps related to forward waiting times with respect to scheduled announcements. The p-values of these two tests present consistent significance. However, both tests lose significance for non-scheduled announcements. There are no consistent significant results observed among all data sets for positive jump sizes related to backward waiting times.

Table 4.10: Means of sizes of positive normalized jumps for Nordic large-cap data. The results are based on all announcements and the filtered data set 1 and 2 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Positive Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	269	13.88	204576	9.945	1.000	7.136E-16***
SWE	214	13.71	99578	10.02	1.000	1.300E-12***
DK	183	13.13	59033	10.17	1.000	2.293E-05***
Non-Scheduled						
FIN	1307	10.82	3328925	9.865	0.99	8.484E-03**
SWE	1363	10.36	3578053	10.13	0.78	0.21
DK	683	11.49	876714	10.35	0.94	5.103E-02
b) Filtered Data Set 1						
Scheduled						
FIN	149	14.50	58860	9.945	1.000	1.351E-10***
SWE	154	14.00	45980	10.03	1.000	1.797E-11***
DK	142	13.98	33871	10.20	1.000	1.016E-07***
Non-Scheduled						
FIN	977	10.32	1869246	9.872	0.89	0.10
SWE	1015	9.836	2019458	10.13	8.392E-02	0.91
DK	569	11.30	600160	10.34	0.95	4.453E-02*
c) Filtered Data Set 2						
Scheduled						
FIN	128	14.54	39638	9.849	1.000	7.961E-09***
SWE	123	14.18	26474	10.06	1.000	3.027E-08***
DK	129	13.65	26589	10.21	1.000	5.051E-06***
Non-Scheduled						
FIN	723	10.01	998327	9.885	0.80	0.19
SWE	669	9.877	803562	10.07	0.25	0.74
DK	410	10.78	305117	10.26	0.65	0.34

Panel B **Backward Positive Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	384	9.799	211153	9.771	0.47	0.52
SWE	234	10.09	105479	9.927	0.59	0.40
DK	205	8.786	62437	10.04	7.994E-04***	99
Non-Scheduled						
FIN	1307	9.850	3388951	9.779	0.83	0.16
SWE	1372	9.849	3889453	10.13	6.471E-02	0.93
DK	752	9.889	945664	10.21	2.978E-02*	0.97
b) Filtered Data Set 1						
Scheduled						
FIN	202	9.458	60789	9.723	6.086E-02	0.93
SWE	174	10.29	49435	9.945	0.84	0.15
DK	156	8.961	36309	10.10	1.982E-02*	0.98
Non-Scheduled						
FIN	965	9.756	1910946	9.777	0.45	0.55
SWE	1031	9.844	2183165	10.11	5.638E-02*	0.94
DK	612	10.09	646287	10.22	0.12	0.87
c) Filtered Data Set 2						
Scheduled						
FIN	163	9.244	40710	9.732	0.15	0.84
SWE	128	9.913	28089	9.888	0.80	0.19
DK	140	8.977	28753	10.15	1.483E-02*	0.98
Non-Scheduled						
FIN	688	9.725	1023933	9.760	0.44	0.55
SWE	661	9.741	861411	10.05	3.715E-03**	0.99
DK	440	9.921	329737	10.14	0.11	0.88

Analysis of Negative Jump Sizes

Table 4.11: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Nordic large-cap data of Sizes of Negative Normalized Jumps. Testing whether the empirical and randomly selected negative normalized jumps come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the jumps with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the negative normalized jumps associated to forward distances and the backward distances. The results are based on all announcements, filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Sizes of Forward Negative Normalized Jumps

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	0.98	1.869E-26***	0.99	1.019E-14***	0.99	7.613E-10***
SWE	0.99	1.619E-15***	0.99	1.589E-09***	0.96	1.620E-06***
DK	0.95	3.315E-05***	0.96	7.765E-06***	0.99	1.368E-05***
Non-Scheduled						
FIN	0.99	3.134E-06***	1.000	2.154E-02*	0.93	0.24
SWE	0.96	2.633E-02*	0.91	0.17	0.44	0.62
DK	0.99	3.162E-04***	0.96	1.013E-03**	0.90	5.583E-03**

Panel B: Sizes of Backward Negative Normalized Jumps

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Scheduled						
FIN	2.517E-03**	0.88	9.266E-02	0.98	2.932E-02*	1.000
SWE	0.83	0.57	0.52	0.48	0.23	0.82
DK	0.34	0.91	7.761E-02*	0.99	0.12	0.99
Non-Scheduled						
FIN	0.89	0.11	0.85	0.38	0.76	0.44
SWE	0.14	0.19	0.10	0.35	0.68	0.83
DK	0.81	0.31	0.64	0.20	0.61	0.35

Table 4.11 shows the results regarding the equality of distribution functions of the sizes for negative normalized jumps between empirical scheduled and non-scheduled announcements and their counterparts in the Nordic markets. The sizes of all positive jumps are excluded.

For jump sizes, which are associated with scheduled announcements and specified with forward distance, there is strong statistical evidence that the empirical distribution function is smaller than the reference one consistently among both filtered and non-filtered data sets. Scheduled announcements tend to predict larger negative jumps compared to general reference announcements. The arrival of a scheduled announcement significantly triggers the occurrence of large negative jumps, which helps in improving the efficiency of markets.

By analyzing the forward normalized negative jump sizes associated with non-scheduled announcements, the empirical distribution function is statistically smaller than the reference distribution function in all Nordic markets with only non-filtered data. However, this finding is not reliable and robust, as no significance is found when filtered data sets 1 and 2 are applied. Compared with forward scheduled announcements, the weaker evidence from non-scheduled announcements reveals weak predictability for future negative jumps

given a non-scheduled news event. This supports the corresponding results when all jump sizes are investigated. If the null hypothesis is not rejected, there will be almost no difference in the distributions of the empirical and reference samples.

For the normalized negative jump sizes, which are associated with scheduled announcements and specified with backward distance, weak evidence is found that the empirical distribution function is higher than reference one in Finland. There is insufficient evidence to refute that the empirical distribution function of jump sizes is identical to the reference one based on data sampling from the Swedish and Danish markets. These findings are not consistent among all data sets.

For the backward normalized jump sizes associated with non-scheduled announcements, no significant p-values are observed. I firmly conclude that there is no statistical difference between the empirical data and the reference data set in the sense of distribution function. This finding underlines the difficulty of utilizing non-scheduled announcements traded by investors beforehand. As a result, forward large negative normalized returns are unrelated to non-scheduled announcements.

Table 4.12 demonstrates the mean test results of normalized negative jumps sizes for Nordic markets. We can observe that the mean values of empirical forward negative jump sizes associated with scheduled announcements are statistically larger than the means of reference samples consistently among the filtered data sets. However, the mean values of empirical positive jump sizes associated with non-scheduled announcements are also statistically larger than the means of the reference data. This empirical property is not consistent among all data sets. For filtered data sets 1 and 2, the Swedish market has no significance.

For backward normalized jump sizes, weak evidence is found for scheduled announcements that the mean values of the empirical sample are statistically smaller than the means of the reference samples only in Denmark. Thus, the Welch U-test results do not enable us to reject that the mean of empirical jump sizes is different from the reference one based on data sampling from the Finnish and Swedish markets. These test results are consistent among all filtered and non-filtered data sets. However, few p-values with statical significance for non-scheduled announcements are observed. The mean of empirical jump sizes associated with scheduled announcements is statistically smaller than the mean of reference samples for Sweden from all data sets. The equality of means between empirical positive jump sizes and the counterparts from the reference data for Finnish and Danish markets is not rejected.

The Welch U mean tests still strongly support our findings from the comparison of distributions via the K-S tests. The p-values of these two tests are consistently significant for scheduled announcements. Furthermore, there are more negative jumps detected from the Finnish and Swedish markets, while more positive jumps are observed from the Danish market than negative ones. A consistent and significant observation among all markets is that the mean sizes of negative jumps are larger than their positive counterparts.

4.3.3 Concluding Remarks

This section investigated the consistency of distributions of empirical data and reference data for normalized jump sizes associated with scheduled and non-scheduled announcements in Nordic markets. Volatility normalized jump sizes are also classified by their signs—that is, positive and negative. Following the same methodology and statistical framework from the previous section, first, scheduled announcements appear to contribute

significantly to the likelihood of generating large jumps after news is delivered. Second, there is almost no statistical relationship between jump sizes and backward non-scheduled announcements, which implies that information leakage hardly proceeds through non-scheduled announcements by the means of jump sizes. Third, negative jumps are observed more than positive jumps for both scheduled and non-scheduled announcements from all Nordic markets. Fourth, the size of negative jumps associated with both scheduled and non-scheduled announcements is, on average, larger than positive jumps. This presents the same strong asymmetry in extremal equity returns in Nordic markets as in the U.S. market, and it is documented in Lahaye et al. (2011). The asymmetry between negative and positive jumps in both amount and sizes might be due to the asymmetry of investors' behavior towards good and bad shocks. If most investors are risk-averse, they react more stronger when they hold a negative expectation to the market than positive. Therefore, market could drop largely and continually after a bad news arrival. Conversely, good news relatively does not stimulate market as effectively as bad news. Statistical analysis provides related phenomenon, e.g. Patton and Sheppard (2015). Finally, the schedulability of announcements triggers investors to change trading strategies, and as a result, prices jump and markets react.

Table 4.12: Means of sizes of negative normalized jumps for Nordic large-cap data. The results are based on all announcements and the filtered data set 1 and 2 that excludes announcements that had another (scheduled or non-scheduled) announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Negative Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	367	16.34	199749	10.94	1.000	1.050E-24***
SWE	234	17.25	101892	14.10	1.000	1.466E-17***
DK	154	14.09	54873	11.47	1.000	2.721E-06***
Non-Scheduled						
FIN	1241	13.01	3160081	10.87	1.000	3.886E-07***
SWE	1384	14.87	3977027	12.90	0.99	3.924E-03**
DK	619	19.30	818534	11.41	0.99	2.733E-04***
b) Filtered Data Set 1						
Scheduled						
FIN	189	16.32	55329	10.90	1.000	7.211E-16***
SWE	153	18.76	48203	13.07	1.000	9.840E-11***
DK	114	15.00	31983	11.61	1.000	4.060E-06***
Non-Scheduled						
FIN	934	11.99	1780780	10.89	0.99	1.676E-03**
SWE	1038	15.84	2195283	13.25	0.89	0.10
DK	509	14.43	563058	11.42	0.99	1.206E-03**
c) Filtered Data Set 2						
Scheduled						
FIN	150	15.61	37621	10.83	1.000	6.517E-11***
SWE	108	13.80	26854	13.83	1.000	1.002E-07***
DK	99	14.80	25696	11.71	1.000	3.207E-05***
Non-Scheduled						
FIN	677	11.33	960526	10.89	0.86	0.13
SWE	614	15.88	843781	13.66	0.32	0.67
DK	363	13.51	290927	11.32	0.98	1.166E-02*

Panel B **Backward Negative Jump Sizes**	**#Obs of** $\|L\|$	**Mean of** $\|L\|$	**#Obs of** $\|\tilde{L}\|$	**Mean of** $\|\tilde{L}\|$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Scheduled						
FIN	252	11.22	193172	11.31	1.167E-03**	0.99
SWE	214	10.24	95991	13.14	0.61	0.38
DK	132	9.377	51469	10.92	0.22	0.77
Non-Scheduled						
FIN	1241	12.67	3100055	11.28	0.94	5.791E-02
SWE	1375	12.63	3665627	12.23	0.37	0.62
DK	550	13.74	749584	10.93	0.81	0.18
b) Filtered Data Set 1						
Scheduled						
FIN	136	11.60	53400	11.57	2.787E-02*	0.97
SWE	133	10.47	44748	12.78	0.53	0.46
DK	100	8.952	29545	11.06	1.207E-02*	0.98
Non-Scheduled						
FIN	946	12.76	1739080	11.32	0.84	0.15
SWE	1022	12.96	2031576	12.56	0.22	0.77
DK	466	14.10	516931	10.88	0.80	0.19
c) Filtered Data Set 2						
Scheduled						
FIN	115	9.189	36549	11.33	1.501E-02*	0.98
SWE	103	9.951	25239	12.38	0.23	0.76
DK	88	8.955	23532	11.41	2.438E-02*	0.97
Non-Scheduled						
FIN	712	11.58	934920	11.22	0.71	0.29
SWE	622	14.39	785932	12.89	0.41	0.58
DK	333	13.76	266307	10.86	0.79	0.20

4.4 Selected Important Announcements in Nordic Markets

This section investigates the statistical association of jumps to five specific important types of announcements in the Finnish, Swedish, and Danish markets. The analysis is within the same test framework introduced in the Chapter 2. However, concrete financial announcements are studied instead of the schedulability of announcements, which was analyzed in the Section 4.1 and 4.2.

The main contribution of this analysis to the finance literature is that not only the statistical association of selected news events to detected jumps but also empirical evidence of Nordic market efficiency partially provided in terms of jumps. From a practical point of view, the values of the selected announcement classes are ranked by market reaction. Since there is vast literature, both theoretical and empirical work, on the mechanism and impacts of merger and acquisition, changes in board composition, and changes in capital structure, I only focus on the market reaction to these particular important announcements in terms of jumps. The waiting times are the main object in this research. Additionally, two comprehensive families of announcements—company announcements and interim reports—are investigated. To the best of my knowledge, there has been little research directly considering the stock prices reacting to company announcements and interim reports in the NASDAQ Nordic database. In particular, interim reports have been found, surprisingly, to be extremely important information resources due to their strong statistical relationship to jumps in stock prices. Empirical findings from the three Nordic markets are presented and related potential economic reasons for these findings are given.

The five selected announcements[1] are

1. **Acquisition**: This class of announcements contains news events on the acquisition activity of one company that is interested in another one. Releases related to acquisitions include all the actions and phases belonging to acquisition processes, from intention to closing. For example, one announcement by Nokia on August 7, 2006 in Helsinki was that Nokia did not recommend or endorse a below-market, mini-tender offer of up to 5 million Nokia ADSs from TRC Capital.

2. **Change in Board Composition**: All the announcements related to personnel changes, resignations, appointments, and retirements in relation to a company's board or management are included. Proposals and nominees for board/committee members are included as well as constitutive meetings of the board. For instance, one announcement by Finnair Oyj on February 28, 2008 was Jaana Tammisto's appointment as managing director of Finland's travel bureau.

3. **Change in Capital Structure**: This family of announcements concerns companies' decisions regarding changes in capital including changes in capital structure and top managerial levels. Releases are related to share offerings, changes in share capital and votes, subscriptions of shares with options and warrants, and the listing of issued options. All actions and phases are included. The following is an example from Novo Nordisk A/S in Copenhagen on December 27, 2010: Novo Nordisk A/S share repurchase program started.

4. **Company Announcement**: All the announcements that do not belong to any of the other categories and general announcements concerning a company's actions are

[1] For more updated announcements, see http://www.nasdaqomxnordic.com/news/companynews

included. Releases in this class include multiple types of information. For example, Elisa's Annual General Meeting was held on Thursday, March 18, 2010, and the information was released by Nasdaq Helsinki. Furthermore, Nordea Bank AB (publ) released a company announcement on March 09, 2007 from Stockholm announcing the completion of its acquisition of Orgresbank.

5. **Interim Report**: Interim reports include financial reports from periods shorter than one year. For instance, KONE Corporation's interim report for January to September 2009 was released on October 20, 2009 at 12:30 p.m. with the following quotation: "KONE further specifies its operating income outlook for 2009. In operating income (EBIT), the objective is EUR 580 – 595 million, excluding the one-time cost of EUR 33.6 million, which was booked in the second quarter. The previous operating income (EBIT) outlook was EUR 570 – 595 million excluding the one-time cost of EUR 33.6 million."

The above five announcement classes were selected with two concerns. One is from the economic/financial viewpoint. Acquisition is one of the most important activities in financial markets. The values of the bidder firm and target company normally both change due to the takeover, as does shareholders' wealth (see (Eckbo, 2008)). Changes in board composition strongly affect managerial performance, which is essential to a firm. The effects of changes in capital structure on asset prices are arguable. Both these news classes—acquisition and change in board composition—are important to financial investors and academia. I also select two comprehensive news classes—company announcements and interim reports. The motivation for selecting these two most frequently released news classes is to investigate the possibility of information leakage and the speed of market reaction in terms of jumps. The other reason is to gain statistical robustness. These five news classes have larger sample sizes than other news.

Particularly, I find the following statistical characteristics. First, for forward distances, all empirical CDFs are not lower than the corresponding reference ones. In particular, tests for company announcements and interim reports strongly indicate the informative releases associated to jumps. Potential information leakage is found to be related to company announcements. Second, forward distances are generally larger than backward ones. Third, CDFs increase sharply in the neighborhood of zero. These two empirical characteristics could reflect the Nordic markets' efficiency to some extent in the aspect of market reaction to particular news releases and insignificant information leakage. Finally, the efficiency of Nordic markets is also partially evinced from the results of the statistical test on changes in capital structure, which to some extent confirms Modigliani and Miller's capital structure theories.

4.4.1 Empirical Results of the Association between Jumps and Selected Announcements

Figure 4.3 plots the CDFs of backward and forward waiting times among the arrival of five important announcements and nearest jumps based on filtered data set 1 for Finnish large-cap companies. It is observable that the difference between empirical distribution (solid line) and reference distribution (dashed line) of forward distances is larger than backward distances for acquisition, change in board composition, company announcement, and interim report, whereas the empirical CDF overlaps the reference CDF for the announcement of changes in capital. In particular, the empirical CDF of forward waiting times related to interim report increases sharply in a small neighborhood of zero and

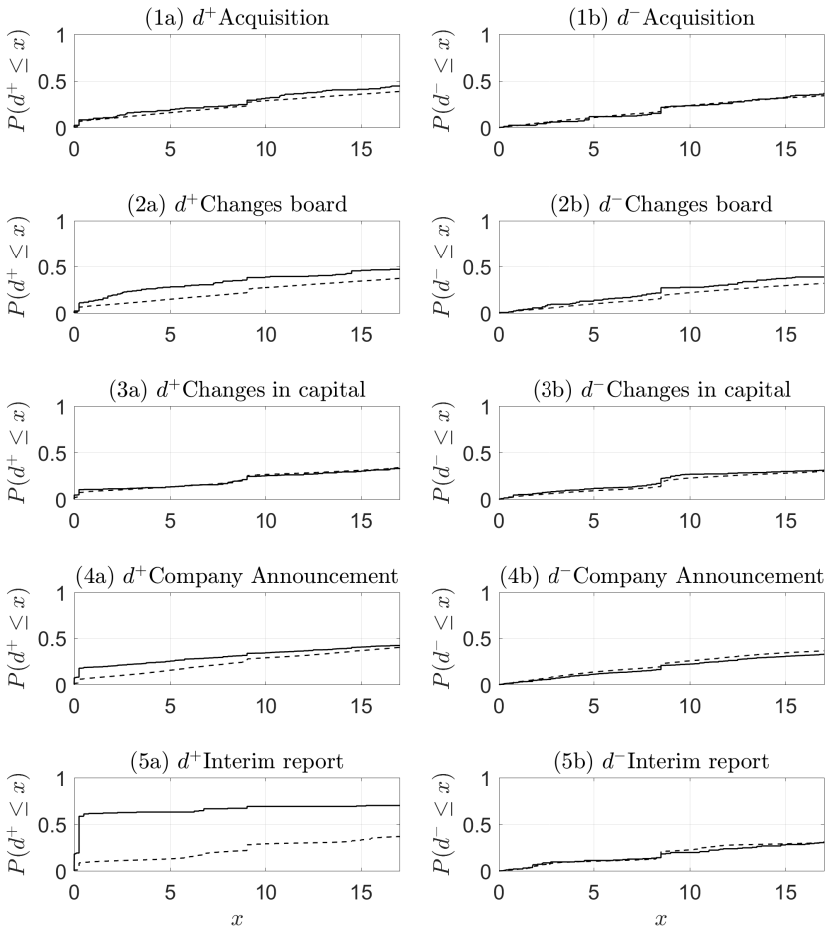

Figure 4.3: CDFs of the distances between the selected announcements and the first detected jumps for Finnish large-cap companies based on filtered data set 1 (excluding announcements that had another announcement in the neighborhood of 6 hours on both sides). d^+ refers to forward distances and d^- to backward distances. Distances are expressed in hours. The solid line plots the CDF based on the actual timestamps (real announcements), and the dashed line represents the reference CDF based on the reference data set, which is generated on the basis of Section 2.2.3.

it jumps to 0.5, which is a distinctively higher level than the corresponding reference CDF. In contrast, the difference between CDFs of backward waiting times is generally negligible. The reference CDFs are observed to be even slightly higher than empirical CDFs. Furthermore, the CDFs step up at 8.5 hours, implying that more observations of waiting times are collected for this particular timestamp, because more announcements arrive in the morning hours just before the market opens.

Table 4.13 presents the p-values of the two-sample K-S test for Finnish large-cap data with selected news including acquisition, change in board composition, change in capital, company announcement, and interim report. For the sake of robustness, I use three data sets: non-filtered data set including all announcements and filtered data sets 1 and 2 that

Table 4.13: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for *Finnish* large-cap data with selected news. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	0.11	0.42	0.19	0.47	0.38	0.27
Changes in board	3.877E-04***	0.91	4.242E-04***	0.94	3.317E-04***	0.98
Changes in capital	0.48	0.46	0.41	0.26	0.43	0.44
Company Announcement	4.731E-23***	7.297E-02	4.616E-17***	4.667E-02*	9.643E-16***	7.127E-02
Interim report	8.084E-60***	0.64	3.290E-48***	0.86	3.184E-48***	0.84

Panel B: Backward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	0.66	0.85	0.52	0.77	0.26	0.91
Changes in board	5.556E-02	0.35	6.871E-02	0.27	7.826E-02	0.30
Changes in capital	0.19	0.98	0.20	0.98	0.34	0.97
Company Announcement	0.94	8.303E-05***	0.98	9.720E-05***	0.99	5.322E-04***
Interim report	0.77	0.61	0.81	0.40	0.85	0.29

exclude announcements that had other announcements in the neighborhoods of 6 and 48 hours on both sides. For forward distances, the empirical CDF is statistically higher than the reference CDF for the following news announcements in the Finnish market: change in board composition, company announcement, and interim report. As for backward distances, the empirical CDF is found to be statistically smaller than the reference one only for company announcement, and this finding has strong significance among all data sets.

As in the previous sections, Welch U-tests for the equality of means of waiting times are also provided as a complementary investigation into the local statistical relationship between empirical waiting times and the reference data. Table 4.14 shows the statistics of the means of waiting times associated with the five classes of news for Finnish large-cap data. The significant mean test results consistently support the K-S test in Table 4.13. First, for forward distances, the empirical mean is significantly different from the corresponding reference one with respect to acquisition, company announcement, and interim report. It is worth noting that the empirical means of waiting time for acquisition and interim report are smaller than the reference counterparts. However, for company announcement, the empirical mean is larger than its reference. Second, for backward distances, only one significant mean test is observed for company announcement, and it shows that the empirical mean of backward waiting times associated with company announcements is statistically larger than its reference.

Figure 4.4 illustrates the CDFs of backward and forward waiting times among the arrival of five important announcements and nearest jumps based on filtered data set 1 for Swedish large-cap companies. It is observed that the distinction between empirical distribution

Table 4.14: Means of waiting times associated to five selected news for Finnish large-cap data. The results are based on all data announcements and the filtered data set 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test**	**Welch U-test**
Forward Distances	d	d	$\tilde{d}$	$\tilde{d}$	**p left tail**	**p right tail**
a) All Data						
Selected News						
Acquisition	181	39.01	30657	36.75	0.37	0.62
Changes in board	185	32.66	30485	37.81	3.120E-03**	0.99
Changes in capital	436	40.70	133715	39.64	0.64	0.35
Company Announcement	1552	35.17	1190484	34.39	1.140E-04***	0.99
Interim report	237	23.54	46969	36.60	1.119E-20***	1.000
b) Filtered Data Set 1						
Selected News						
Acquisition	171	38.62	27012	36.62	0.39	0.60
Changes in board	181	30.40	28164	36.89	1.436E-03**	0.99
Changes in capital	415	41.91	127649	40.20	0.79	0.20
Company Announcement	1281	36.16	855195	34.60	7.927E-03**	0.99
Interim report	198	22.73	35000	37.50	7.482E-19***	1.000
b) Filtered Data Set 2						
Selected News						
Acquisition	158	40.60	21860	36.42	0.65	0.34
Changes in board	177	29.93	27019	36.75	1.170E-03**	0.99
Changes in capital	393	41.87	119586	40.45	0.69	0.30
Company Announcement	1067	35.69	656970	35.08	5.608E-03**	0.99
Interim report	196	22.47	34340	36.90	6.541E-19***	1.000

Panel B	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test**	**Welch U-test**
Backward Distances	d	d	$\tilde{d}$	$\tilde{d}$	**p left tail**	**p right tail**
a) All Data						
Selected News						
Acquisition	181	38.24	30657	38.81	0.36	0.63
Changes in board	185	39.10	30485	40.19	0.2.277	0.77
Changes in capital	436	39.13	133715	41.56	5.869E-02	0.94
Company Announcement	1552	39.53	1190484	35.42	1.000	1.842E-05***
Interim report	237	40.70	46969	40.07	0.60	0.39
b) Filtered Data Set 1						
Selected News						
Acquisition	171	36.93	27012	38.76	0.35	0.64
Changes in board	181	39.67	28164	39.91	0.30	0.69
Changes in capital	415	39.70	127649	41.80	7.779E-02	0.92
Company Announcement	1281	40.32	855195	35.83	1.000	1.203E-05***
Interim report	198	40.39	35000	39.88	0.67	0.32
b) Filtered Data Set 2						
Selected News						
Acquisition	158	35.50	21860	39.20	0.19	0.80
Changes in board	177	39.85	27019	39.98	0.31	0.68
Changes in capital	393	40.44	119586	42.12	0.15	0.84
Company Announcement	1067	41.07	656970	36.28	1.000	1.863E-05***
Interim report	196	40.71	34340	39.27	0.78	0.21

(solid line) and reference distribution (dashed line) of forward distances is more obvious than backward distances for acquisition, company announcement, and interim report, whereas the empirical CDF overlaps the reference CDF for the announcement of changes in capital and board composition. Particularly, the empirical CDF of forward waiting times related to interim report increased dramatically in near zero and it jumps to 0.6, a distinctively higher level than the corresponding reference CDF. However, the difference

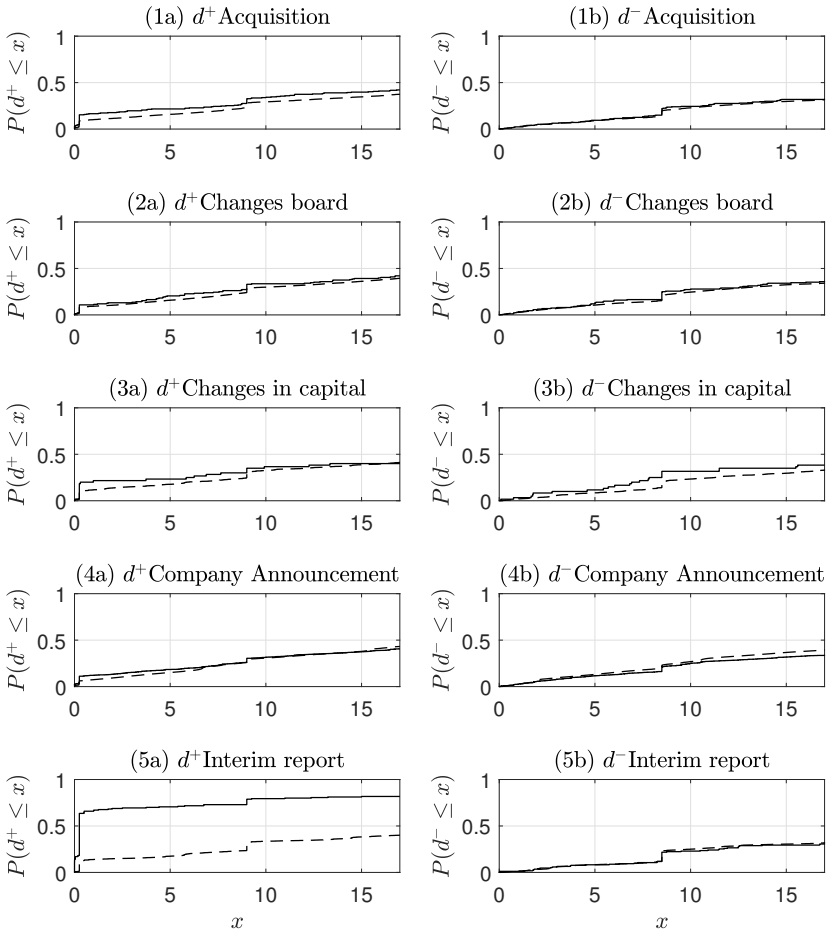

Figure 4.4: CDFs of the distances between the selected announcements and the detected jumps for Swedish large-cap companies based on filtered data set 1 (excluding announcements that had another announcement in the neighborhood of 6 hours on both sides). d^+ refers to forward distances and d^- to backward distances. Distances are expressed in hours. The solid line plots the CDF based on the actual timestamps (real announcements), and the dashed line represents the reference CDF based on the reference data set, which is generated on the basis of Section 2.2.3.

between CDFs of backward waiting times is generally negligible. The reference CDFs are observed to be slightly higher than empirical CDFs of company announcements. Additionally, the CDFs step up at 8.5 hours, since more observations of waiting times are collected for this particular timestamp, because more announcements arrive in the morning hours just before the market opens.

Table 4.15 illustrates the p-values of the two-sample K-S test for Swedish large-cap data with selected news including acquisition, change in board composition, change in capital, company announcement, and interim report. For robustness, I implement three data sets: non-filtered data set including all announcements and filtered data sets 1 and 2 that exclude announcements that had other announcements in the neighborhoods of 6 and 48

Table 4.15: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for *Swedish* large-cap data with selected news. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	6.122E-02	0.59	6.914E-02	0.82	7.026E-02	0.72
Changes in board	0.17	0.84	0.32	0.60	0.27	0.63
Changes in capital	0.26	0.20	0.29	0.69	0.18	0.81
Company Announcement	2.548E-06***	1.199E-04***	2.811E-04***	8.012E-03**	9.427E-04***	6.723E-02
Interim report	2.993E-45***	0.98	8.172E-45***	0.98	8.172E-45***	0.98

Panel B: Backward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	0.41	0.95	0.52	0.97	0.52	0.91
Changes in board	0.78	0.24	0.57	0.74	0.52	0.65
Changes in capital	4.512E-02*	0.11	0.16	0.35	0.11	0.50
Company Announcement	0.86	1.111E-07***	0.95	2.105E-07***	0.84	4.899E-05***
Interim report	4.831E-03**	0.88	4.280E-03**	0.76	4.280E-03**	0.76

hours on both sides. For forward distances, the empirical CDF is tested statistically above the reference CDF for the following news in the Swedish market: company announcement and interim report. However, for backward distances, the empirical CDF is statistically smaller than the reference one only for company announcement, and vice versa for interim report. All tests discussed above have strong significance among all data sets.

Welch U-tests for the equality of means of waiting times are also shown as an additional focus on the local statistical relationship between empirical waiting times and the reference data. Table 4.16 shows the statistics of means of waiting times associated with the five classes of selected news for Swedish large-cap data. The significant mean test results partially support the K-S test in Table 4.15. First, for forward distances, the empirical mean is significantly different from the corresponding reference one with respect to interim report. It is observed that the empirical means of waiting time for interim report are smaller than the reference counterpart. Second, for backward distances, only one significant mean test is observed for company announcement, and it shows that the empirical mean of backward waiting times associated with company announcements is statistically larger than its reference.

Figure 4.5 shows the CDFs of backward and forward waiting times between the arrival of five important announcements and nearest jumps based on filtered data set 1 for Danish large-cap companies. The difference between the empirical distribution (solid line) and reference distribution (dashed line) of forward distances is larger than backward distances for acquisition, change in board composition, change in capital, company announcement, and interim report. As in Figure 4.3 and Figure 4.4, the empirical CDF of forward waiting times related to interim report increases sharply in a small neighborhood of

Table 4.16: Means of waiting times associated to five classes of selected news for Swedish large-cap data. The results are based on all data announcements and the filtered data set 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test**	**Welch U-test**
Forward Distances	d	d	$\tilde{d}$	$\tilde{d}$	**p left tail**	**p right tail**
a) All Data						
Selected News						
Acquisition	266	35.66	60960	36.83	0.20	0.79
Changes in board	186	32.80	31265	33.70	0.18	0.81
Changes in capital	68	29.77	4449	33.48	0.44	0.55
Company Announcement	2082	33.19	1753208	30.62	0.94	5.146E-02
Interim report	176	15.14	27343	33.48	6.136E-27***	1.000
b) Filtered Data Set 1						
Selected News						
Acquisition	254	34.97	58526	37.34	0.13	0.86
Changes in board	176	34.14	28044	33.69	0.37	0.62
Changes in capital	60	27.60	3497	32.94	0.24	0.75
Company Announcement	1602	33.51	1138323	31.15	0.87	0.12
Interim report	170	14.24	26011	33.54	3.535E-28***	1.000
b) Filtered Data Set 2						
Selected News						
Acquisition	234	34.97	47290	37.13	0.14	0.85
Changes in board	170	33.78	26211	33.40	0.35	0.64
Changes in capital	56	27.25	3078	32.76	0.17	0.82
Company Announcement	1083	34.17	630577	31.83	0.63	0.36
Interim report	170	14.24	26011	33.54	3.535E-28***	1.000

Panel B	**#Obs of**	**Mean of**	**#Obs of**	**Mean of**	**Welch U-test**	**Welch U-test**
Backward Distances	d	d	$\tilde{d}$	$\tilde{d}$	**p left tail**	**p right tail**
a) All Data						
Selected News						
Acquisition	266	36.37	60960	39.96	0.13	0.86
Changes in board	186	42.07	31265	35.61	0.69	0.30
Changes in capital	68	41.16	4449	36.44	0.43	0.56
Company Announcement	2082	35.81	1753208	31.72	1.000	7.407E-07***
Interim report	176	29.18	27343	36.53	3.540E-02*	0.96
b) Filtered Data Set 1						
Selected News						
Acquisition	254	36.95	58526	39.91	0.24	0.75
Changes in board	176	36.71	28044	35.59	0.38	0.61
Changes in capital	60	40.92	3497	36.56	0.48	0.51
Company Announcement	1602	36.58	1138323	32.31	1.000	5.105E-07***
Interim report	170	29.44	26011	36.46	6.314E-02	0.93
b) Filtered Data Set 2						
Selected News						
Acquisition	234	37.42	47290	39.31	0.31	0.68
Changes in board	170	36.93	26211	35.52	0.37	0.62
Changes in capital	56	36.57	3078	35.37	0.34	0.65
Company Announcement	1083	35.85	630577	32.71	0.99	6.668E-04***
Interim report	170	29.44	26011	36.46	6.314E-02	0.93

zero and it jumps to 0.6, which is a rather higher level than the corresponding reference CDF. Conversely, the differences between CDFs of backward waiting times are generally negligible. The reference CDFs are observed to be slightly higher than empirical CDFs of company announcement and interim report. Furthermore, the CDFs jumping at 8.5 hours for more observations of waiting times are collected at this particular timestamp, because more announcements arrive in the morning hours just before the market opens.

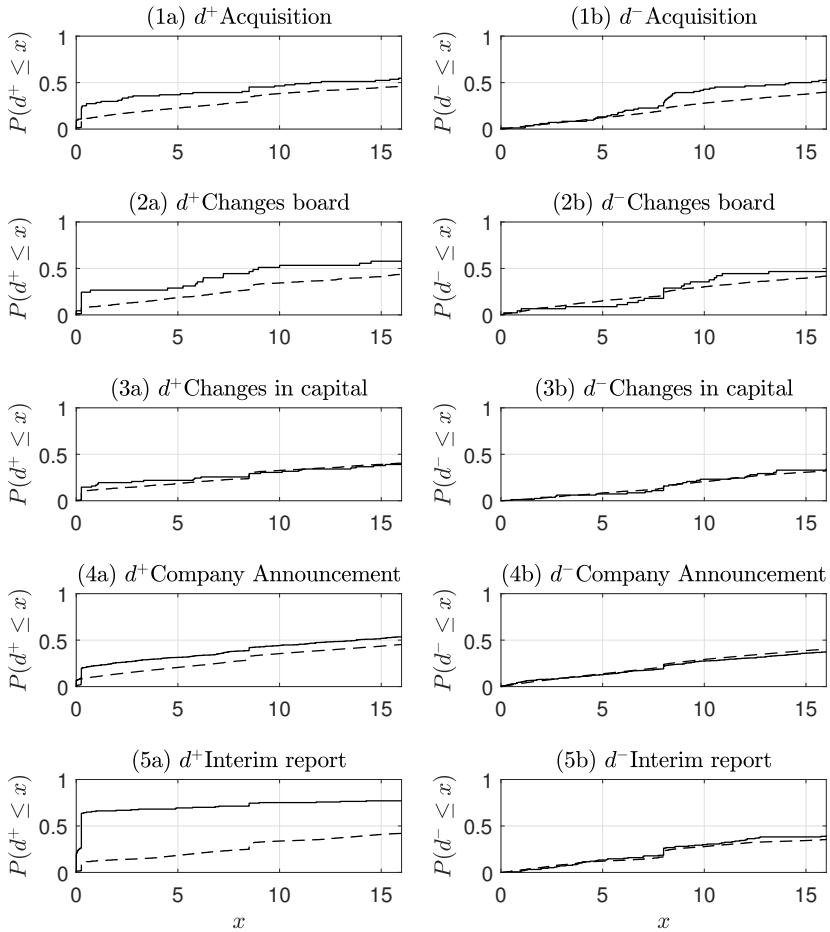

Figure 4.5: CDFs of the distances between selected announcements and detected jumps for Danish large-cap companies based on filtered data set 1 (excluding announcements that had another announcement in the neighborhood of 6 hours on both sides). d^+ refers to forward distances and d^- to backward distances. Distances are expressed in hours. The solid line plots the CDF based on the actual timestamps (real announcements), and the dashed line represents the reference CDF based on the reference data set, which is generated on the basis of Section 2.2.3.

Table 4.17 illustrates the p-values of the two-sample K-S test for Danish large-cap data with selected news including acquisition, change in board composition, change in capital, company announcement, and interim report. For the sake of robustness, I implement three data sets: non-filtered data set including all announcements and filtered data sets 1 and 2 that exclude announcements that had other announcements in the neighborhoods of 6 and 48 hours on both sides.

For forward distances, the empirical CDF is statistically higher than the reference CDF for the following news in the Danish market: acquisition, change in board composition, company announcement, and interim report, whereas for backward distances, the empirical CDF is statistically smaller than the reference one only for acquisition with strong

Table 4.17: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for *Danish* large-cap data with selected news. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively.

Panel A: Forward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	2.551E-03**	1.00	4.756E-03**	1.000	6.865E-03**	1.00
Changes in board	1.786E-02*	0.78	2.151E-02*	0.77	2.151E-02*	0.77
Changes in capital	0.56	0.24	0.40	0.25	0.36	0.21
Company Announcement	2.014E-11***	0.53	7.258E-11***	0.67	1.424E-10***	0.64
Interim report	1.603E-42***	1.00	5.718E-41***	1.000	5.347E-41***	1.00

Panel B: Backward Distances

	a) All Data		b) Filtered Data Set 1		c) Filtered Data Set 2	
	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
Selected News						
Acquisition	8.071E-03**	0.83	6.817E-03**	0.94	3.965E-02*	0.96
Changes in board	0.38	0.42	0.20	0.58	0.20	0.58
Changes in capital	0.40	0.61	0.36	0.86	0.23	0.88
Company Announcement	0.25	1.467E-02*	0.50	5.020E-02	0.55	6.855E-02
Interim report	0.31	0.90	0.37	0.85	0.32	0.93

significance among all data sets.

Similar to the previous sections, Welch U-tests for the equality of means of waiting times are also presented to reveal the local statistical relationship between empirical waiting times and the reference data. Table 4.18 shows the statistics of the means of waiting times associated with the five classes of selected news for Danish large-cap data. The significant mean test results consistently support the K-S test in Table 4.17. First, for forward distances, the empirical mean is shown to be significantly different from the corresponding reference one with respect to acquisition, change in board composition, company announcement, and interim report. Moreover, the empirical means of waiting time for acquisition, change in board composition, company announcement, and interim report are all smaller than the reference counterparts. Second, for backward distances, only one significant mean test is observed for acquisition, and it shows that the empirical mean of backward waiting times associated with company announcements is statistically smaller than its reference.

Table 4.18: Means of waiting times associated to five classes of selected news for Danish large-cap data. The results are based on all data announcements and the filtered data set 1 and 2 that exclude announcements that had another announcement in the neighborhood of 6 (Filtered data set 1) and 48 (Filtered data set 2) hours on both sides, respectively. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Distances**	**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Selected News						
Acquisition	102	17.30	10318	25.68	2.609E-03**	0.99
Changes in board	49	27.53	2401	29.44	2.406E-02*	0.97
Changes in capital	90	33.42	7815	27.90	0.72	0.27
Company Announcement	859	24.73	601395	26.27	2.735E-06***	1.000
Interim report	170	11.84	27849	28.83	1.408E-24***	1.000
b) Filtered Data Set 1						
Selected News						
Acquisition	84	17.85	7025	27.22	2.459E-03**	0.99
Changes in board	45	28.57	1961	29.28	3.989E-02*	0.96
Changes in capital	82	33.94	6710	28.78	0.61	0.38
Company Announcement	759	24.44	466731	26.19	4.113E-06***	1.000
Interim report	157	11.96	22508	28.43	7.559E-22***	1.000
b) Filtered Data Set 2						
Selected News						
Acquisition	69	18.10	4652	28.68	3.657E-03**	0.99
Changes in board	45	28.57	1961	29.28	3.989E-02*	0.96
Changes in capital	77	34.53	5833	28.90	0.61	0.38
Company Announcement	600	25.04	319405	26.78	3.556E-05***	1.000
Interim report	155	12.10	23065	28.63	1.233E-21***	1.000

Panel B **Backward Distances**	**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
Selected News						
Acquisition	102	24.51	10318	28.88	1.366E-02*	0.98
Changes in board	49	25.05	2401	28.58	0.45	0.54
Changes in capital	90	30.54	7815	32.52	0.51	0.48
Company Announcement	859	30.99	601395	28.53	0.97	2.565E-02*
Interim report	170	29.96	27849	31.25	0.28	0.71
b) Filtered Data Set 1						
Selected News						
Acquisition	84	23.86	7025	30.90	4.349E-03**	0.99
Changes in board	45	22.99	1961	29.72	0.10	0.89
Changes in capital	82	29.34	6710	32.83	0.26	0.73
Company Announcement	759	31.08	466731	28.59	0.97	2.748E-02*
Interim report	157	29.93	22508	30.92	0.33	0.66
b) Filtered Data Set 2						
Selected News						
Acquisition	69	26.01	4652	31.27	2.136E-02*	0.97
Changes in board	45	22.99	1961	29.72	0.10	0.89
Changes in capital	77	29.20	5833	32.86	0.27	0.72
Company Announcement	600	31.44	319405	28.83	0.97	2.453E-02*
Interim report	155	30.06	23065	31.37	0.27	0.72

4.4.2 Discussion on Main Empirical Findings for Selected Announcements

Taking an overview of the empirical findings among the three Nordic markets, the following statistical characteristics are found. First, for forward distances, all empirical CDFs are above the corresponding reference CDFs. Second, forward distances are generally larger

than backward ones. Third, CDFs increase sharply in the neighborhood of zero. Lastly, interim report has the largest difference among the three markets. In addition, there are also notable anomalies among the three markets. Backward empirical CDFs are not always above the corresponding reference ones, for example, acquisition and change in board composition in the Danish market. Furthermore, announcements of changes relating to boards affect the Finnish and Danish markets more strongly than the Swedish market. Interestingly, none of the markets reacts to the release of changes in capital at a statistically significant level.

I attempt to concisely provide some potential interpretations of the empirical findings related to each class of selected news. For the announcements of **Acquisition**, the stock prices normally jump due to the acquisition premium of a takeover. Empirically, the prices of the target company increase because of certain benefits, such as economies of scale and scope and potential monopoly gains after the takeover, and the announcement reaction of the target company is generally positive and larger than the bidder. A detailed empirical survey is provided in Chapter 15 of Eckbo (2008). This mechanism is empirically supported by the K-S test for forward waiting times among the three Nordic markets. The findings are in the line with Mandelker (1974), Huang and Walkling (1987), and Moeller et al. (2005), who investigated the abnormal returns of a target company and the bidders' changes in wealth. Moreover, there is almost no difference in backward waiting times between the empirical and reference CDFs. This implies that there is possibly no significant information leakage regarding acquisition announcements in Nordic markets. This might be owing to strict insider supervision and external supervision from the SEC. Bris (2005) claimed that laws against insider trading work for reducing the incentive to commit illegal insider trading based on empirical data on global takeovers. Compared with other selected news classes, the average of forward waiting times of acquisition is relatively longer. One possible reason is the existence of takeover defenses against hostile acquisition. Another likely practical reason for longer jump waiting times could be tax and accounting investigations.

Change in board composition are crucial to the top management of a company. Any essential changes in board composition should influence firm performance. Warner et al. (1988) provided empirical evidence from the U.S. market that extremely poor stock performance will lead to changes in board composition. Conversely, no significant reverse relationship was identified by applying traditional event study methodology. However, other studies have put forward the opposite view. Hermalin and Weisbach (1991) investigated differences in firm performance caused by board composition and ownership structure. They found no relationship between board composition and performance. The impact of changes in board structure on firm performance and stock prices seems uncertain. Some reasons could be the sizes of markets and how the changes to boards directly influence CEOs. The releases of negative changes to boards may affect the managerial performance and inventiveness of CEOs. As a result, investors may sell their shares of the company. Shivdasani and Yermack (1999) found that stock prices react weakly to independent director appointments when the CEO is involved in director selection. In particular, related studies on Nordic markets show a different picture. Ahern and Dittmar (2012) analyzed Norwegian companies to identify the impact of corporate boards on company value. They found that changes to the ratio of men to women on boards led to a significant decline in Tobin's Q. Additionally, changes in board composition served to maximize shareholder value.

The findings of this thesis support the importance of news announcements to changes

in board composition, especially in the Finnish and Danish markets. However, there is no such evidence for the Swedish market. Randøy and Nielsen (2002) examined the relationships between board size, CEO compensation, and company performance. They found that changes in board sizes have a positive impact on CEO compensation, which has no significant relationship with company performance. These findings may partially explain why Swedish large-cap stock prices have no significant reactions to announcements about changes in board composition in terms of jumps. Additionally, there is no prominent information leakage related to changes in board composition. This might be due to well-controlled board meetings and internal rules. For the same reason, Nordic markets react to changes in company boards with a certain period of delay. To most investors, the content and consequences of board meetings are hard to predict.

The impact of **Changes in capital** on firm performance and stock prices has been widely discussed for several decades, especially Modigliani and Miller's benchmark capital structure theories starting from Modigliani and Miller (1958), according to which the market value of a company mainly relates to its earning power and the risk of its underlying assets, rather than the way it chooses to finance its investments or distribute dividends. However, this conclusion was derived from the complete-market assumption, which is usually rejected in the empirical literature. Myers (1984) documented the difficulty of testing whether the relationship between financial leverage and investors' required return is consistent with the pure Modigliani – Miller capital structure theories. Strebulaev (2007) showed empirically that the value of a firm relates to its capital structure in a dynamic economy. Despite many inconsistent findings relating to Modigliani and Miller's theories, there is no empirical evidence in this research illustrating a strong impact of changes in firm capital on market values in terms of jumps in stock prices. The statistical test result in this thesis not only provides empirical support for Modigliani and Miller's capital structure theories but also partially shows the efficiency of Nordic markets.

Company announcement contain various types of idiosyncratic information by definition. The statistical test results reveal that company announcement is one of the most informative classes of news for investors. Jumps are significantly associated with this class. Importantly, information leakage exists in company announcements, which is the only class with this property out of the five selected classes. The K-S test for backward waiting times highlights information leakage.

Finally, **Interim report** is found to be the most attractive release to investors, for significant jumps most closely follow these announcements compared to other news arrivals. Statistically, there is no doubt about the association between releases of interim reports and detected jumps due to the valuable and varied information contained in these reports to investors. All three Nordic markets are sensitive to the arrival of this type of news. The results support the empirical finance literature on the importance of company interim reports. For example, Kiger (1972) found that investors use interim reports for predicting annual income. The interim reports include a large amount of earning announcements, which are investigated deeply to determine their relation to jumps. For instance, Lee and Mykland (2008) and Maheu and McCurdy (2004) presented links between earning announcements and jumps from testing and modeling points of view. Additionally, the average forward waiting time of interim report to jumps is the shortest among the selected news events. This empirical characteristic, together with the largest difference between empirical and reference CDFs, indicates the value of interim reports to markets' effectiveness.

4.4.3 Concluding Remarks

This section presented the statistical analysis of waiting times for five typical classes of announcements. Three important individual news events—acquisition, change in board composition, and change in capital, were selected. Two additional comprehensive news classes investigated were company announcement and interim report on the purpose of testing information leakage and market efficiency.

In conclusion, the empirical results for acquisition are inconsistent with existing literature. The observed longer waiting times may result from takeover defenses. Change in board composition evinces different levels of significance in the Nordic markets, indicating idiosyncratic information digestion. Forthcoming changes to boards drive the Finnish and Danish markets harder than in the case of the Swedish market. In addition, the efficiency of Nordic markets is revealed by the insignificant association between changes in capital and jumps across the three markets and the prominent, large difference in CDFs of forward waiting times for interim report. Moreover, stock prices jump actively and promptly after interim report releases in all three Nordic markets.

5 Application of U.S. News Announcements

5.1 Application of U.S. News Announcements on Nordic Stock Markets

U.S. macro announcements, which contain real-time macroeconomic statistics including domestic output, employment, change of prices, imports and exports, consumption, and so on, play an important role in inspecting and revising the quality of the economy both domestically and internationally. However, it is not only economists and governmental analysts who care about these seasonal economic indicators; investors and traders also take advantage of the information from macroeconomic releases in their trading activities, as various U.S. macro announcements influence financial markets in a significant way. For instance, Castanias (1979) empirically showed that the arrival of macro information affects stock prices and partially determines the statistical distribution of stock returns. Berry and Howe (1994) constructed a measure for public macroeconomic information flow and suggested that there is a positive and moderate relationship between public information and trading volume. Macroeconomic announcements also impact the volatility of asset prices. Andersen and Bollerslev (1998) studied five-minute Deutsche mark−dollar exchange rates and documented that macroeconomic announcements link to large returns and affect the daily pattern of volatility. Andersen et al. (2003) found that macro announcements lead jumps in the conditional mean of returns. The measurement of macro announcements is not the timestamps but the difference between realized and expected macro variables.

Besides the effects of U.S. macro announcements on the domestic market, there is literature documenting the impact of U.S. macroeconomic releases on international financial markets: Nikkinen et al. (2006) investigated the behavior of volatility around the releases of U.S. macroeconomic news for G7 countries, non-G7 European markets, and Asian markets. They found that these markets all react to U.S. macroeconomic news in an integrated manner. Nikkinen and Sahlström (2004) compared the influence of domestic and U.S. macroeconomic news on implied volatility in the German and Finnish stock markets. They documented that U.S. news seems more important than domestic news in the sense of moving stock prices. Albuquerque and Vega (2008) examined how domestic and U.S. news about macroeconomic fundamentals relate to the co-movement of returns between U.S. and Portuguese stock prices. The authors focused on the earning announcements and showed that there is no significant effect of earning news on market co-movement.

One study that closely resembles this one is that of Délèze and Hussain (2014), who studied the impact of U.S. macroeconomic news on European stock markets and showed

that U.S. macroeconomic announcements cause significant jumps on the main European stock indices, currency, and interest rate futures. However, our research is distinct from that of Délèze and Hussain (2014) in the following aspects. First, I focus on the reaction of equity prices to macroeconomic releases instead of using market indices. Taking direct insight into individual stock prices not only reveals the idiosyncratic characteristics of different sized companies but also automatically provides us larger samples, which are essential for making statistical inferences. Second, the statistical framework based on waiting times allows for extracting the properties of distribution in a more formal and direct way. Third, I attentively consider the impacts on three Nordic exchanges: Helsinki, Stockholm, and Copenhagen.

In this section, the impact of U.S. macroeconomic announcements on Nordic markets in terms of jumps is investigated. In particular, I attempt to answer the following two questions:

1. Generally, do equities in Nordic markets react according to U.S. macroeconomic announcements in terms of jumps?
2. If so, which arrival times of macro announcements may easily trigger jumps in Nordic markets?

In contrast to investigating the impact of certain types of announcements, I consider and focus on the announcement timestamps (timings) of macroeconomic announcements, since the U.S. macro announcement sample reveals that there is a strong overlapping effect. For instance, CPI, Import Price Index, Personal Income and, Nonfarm Productivity are normally announced at the same time (U.S. Eastern Daylight Time [EDT])—that is, 8:30 a.m. Therefore, instead of considering some important individual macroeconomic announcements, I consider the macroeconomic releases at essential clock times. The U.S. macroeconomic announcement data set overall consists of 133 types of announcements released within the period January 02, 2006 to December 31, 2010. To measure the effect of these announcements from the U.S. market on Nordic equities, timestamps must be transformed from EDT to CEST and classified according to the announcement clock time. EDT and CEST are both adjusted according to the winter−summer switch, making the timestamps of announcements and Nordic market time consistent. I select the following U.S. important announcement timings (EDT): 12:00 a.m., 7:00 a.m., 8:30 a.m., 9:00 a.m., 9:45 a.m., 10:00 a.m., 2:00 p.m., and 5:00 p.m. These are the clock times at which the U.S. macroeconomic announcements arrive most frequently.

From the p-values of the K-S and Welch tests, the following main empirical evidence emerges. First, the three Nordic markets in our sample react significantly to the arrivals of U.S. macroeconomic announcements. Second, macroeconomic releases of essential announcement timings impact the Nordic stock prices in terms of jumps, especially at 1:00 p.m., 3:45 p.m., and 11:00 p.m. CEST. These findings are along the lines of Délèze and Hussain (2014) and Nikkinen and Sahlström (2004). Additionally, Ammer et al. (2010) focused on U.S. monetary policy shocking global stock markets including Nordic countries.

5.1.1 Aggregated Macroeconomic News

This subsection provides the results of the K-S and Welch U tests, aiming to show the general impact of U.S. macroeconomic releases on Nordic markets in terms of jumps.

One difference between this section and previous sections is that the sample size of the reference data set of announcements is not the square of but 10 times the sample size of the empirical data set. In practice, I hope to obtain relatively more simulated reference announcement timestamps given an acceptable computational time. However, following the rule of thumb in Bera et al. (2013) to set the size of the reference sample of waiting times to be the square of the empirical data set means suffering from an extremely long simulation time. Therefore, I reduce the reference sample size to 10 times the empirical data set. Practically, this treatment does not harm the power of statistical tests.

Table 5.1: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Aggregated U.S. Macroeconomic News on Nordic Markets. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are of 10 iterations. For each iteration, we simulate the same number of empirical announcements. All timestamps of announcements are transformed from U.S. EDT (U.S. Eastern Daylight Time) to CEST (Central European Summer Time). Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data sets 1 that excludes announcements that had another Macro-announcement in the neighborhood of 6 hours on both sides.

Panel A: Forward Distances

	a) All Data		**b) Filtered Data Set 1. No other announcements within 6 h on both sides**	
	h_a: **larger**	h_a: **smaller**	h_a: **larger**	h_a: **smaller**
Market				
FIN	3.340E-83***	5.436E-02	1.534E-09***	0.14
SWE	1.128E-107***	5.527E-02	2.750E-22***	0.53
DK	5.953E-86***	0.18	3.281E-16***	0.41

Panel B: Backward Distances

	a) All Data		**b) Filtered Data Set 1. No other announcements within 6 h on both sides**	
	h_a: **larger**	h_a: **smaller**	h_a: **larger**	h_a: **smaller**
Market				
FIN	1.852E-02*	1.592E-41***	0.62	3.818E-12***
SWE	6.340E-05***	1.216E-61***	6.351E-03***	9.342E-18***
DK	1.424E-03**	1.278E-33***	0.11	4.342E-13***

Table 5.1 presents the results of the K-S tests for waiting times between the arrivals of U.S. macroeconomic announcements, whose timestamps are transformed to CEST, and jumps detected in Nordic stock prices. The results only consist of p-values using all U.S. macro announcements and filtered data set 1 of the announcements, excluding other announcements within the neighborhood of 6 hours on both sides. Filtered data set 2 with a window of 48 hours is not presented, since filtered data sets 1 and 2 give the same sample. This is due to the regularity of U.S. macroeconomic announcements; for example, the CPI core index is released regularly on the second Wednesday of every month.

The K-S tests show that the empirical CDFs of forward distances are statistically higher than their counterparts from the reference samples, whereas empirical CDFs are lower than the reference CDFs of backward waiting times. The observation above is uniform among Finnish, Swedish, and Danish markets. Regarding the conclusions relating to statistical significance, the importance of announcement data filtering is apparent. When all macro announcements are applied, for backward waiting times, the two opposite alternative hypotheses both have significantly small p-values, even though the hypothesis that the empirical CDFs are smaller than the reference CDFs provides much more significance. This might be ambiguous for interpretation. However, the difference in significance of the

Table 5.2: Means of Waiting Times with All Macro News Arrival for Nordic large-cap data. The results are based on all data announcements and the filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Distances**	**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
All Macro News						
FIN	58027	38.90	580270	38.61	4.595E-06***	1.000
SWE	56650	35.17	566500	34.97	1.596E-07***	1.000
DK	40402	28.44	404020	28.44	1.102E-10***	1.000
b) Filtered Data Set 1						
All Macro News						
FIN	14907	38.52	149070	38.32	7.273E-02	0.92
SWE	14608	34.32	146080	34.41	3.236E-03**	0.99
DK	10477	28.24	104770	28.01	8.256E-02	0.91
Panel B **Backward Distances**	**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
a) All Data						
All Macro News						
FIN	58027	43.20	580270	43.31	0.99	9.317E-03**
SWE	56650	39.14	566500	39.04	0.99	1.342E-04***
DK	40402	32.74	404020	32.70	0.98	1.062E-02*
b) Filtered Data Set 1						
All Macro News						
FIN	14907	43.96	149070	43.64	0.99	2.486E-03**
SWE	14608	40.94	146080	40.91	0.95	4.727E-02*
DK	10477	33.99	104770	34.33	0.89	0.10

two assumptions turns distinctively when filtered data set 1 is adopted.

The results of the complementary mean tests reported in Table 5.2 surprisingly show the opposite picture. The empirical means of forward (backward) waiting times are larger (smaller) than the corresponding reference ones for the three Nordic markets. This seems to oppose the K-S test, implying that there is no significant impact from U.S. macroeconomic announcements on Nordic markets. Nevertheless, I can state reluctantly that the conclusion is reliable, as the Welch U test is a location test instead of a uniform test, like the K-S test.

The significant reaction of Nordic stock prices to the U.S. market is not a new finding; see existing related research, such as Délèze and Hussain (2014) and Chan et al. (2017). However, the statistics reveal the relationship between extremal returns (jumps) and U.S. macroeconomic announcements via waiting times. To the best of my knowledge, this is a new contribution to the finance literature.

5.1.2 Macro News Announcements at Specific Timings

Table 5.3 reports the K-S test results for the impact of the arrivals of U.S. macroeconomic announcements on the Finnish market at eight typical timings, in the sense of waiting time to jumps. The macroeconomic releases at the following timings in CEST are shown to have a higher empirical CDF than their reference counterparts for forward waiting times: 1:00 p.m., 3:00 p.m., 3:45 p.m., 8:00 p.m., and 11:00 p.m., while the announcements made at 6:00 a.m. and 2:30 p.m. generate relatively lower empirical CDFs than the reference one.

Table 5.3: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Macro News Arrive at Significant Timings (U.S. EDT) on Finnish Markets. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides.

Panel A: Forward Distances

		a) All Data		b) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
EDT	**CEST**				
12:00 AM	6:00 AM	0.76	4.144E-03**	0.67	3.051E-02*
7:00 AM	1:00 PM	2.410E-06***	0.33	3.455E-07***	0.73
8:30 AM	2:30 PM	0.83	1.471E-04***	1.000	2.821E-04***
9:00 AM	3:00 PM	6.689E-03**	0.53	6.689E-03**	0.53
9:45 AM	3:45 PM	1.896E-02*	0.40	1.896E-02*	0.40
10:00 AM	4:00 PM	0.86	0.23	0.17	0.26
2:00 PM	8:00 PM	9.843E-03**	0.82	0.32	0.93
5:00 PM	11:00 PM	1.453E-06***	0.98	1.453E-06***	0.98

Panel B: Backward Distances

		a) All Data		b) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
EDT	**CEST**				
12:00 AM	6:00 AM	1.050E-02*	0.65	1.442E-02*	0.89
7:00 AM	1:00 PM	0.38	2.532E-02*	0.40	3.497E-02*
8:30 AM	2:30 PM	9.486E-05***	0.98	0.18	3.595E-04***
9:00 AM	3:00 PM	0.22	0.38	0.22	0.38
9:45 AM	3:45 PM	0.11	0.52	0.11	0.52
10:00 AM	4:00 PM	0.51	9.289E-02	2.580E-05***	0.99
2:00 PM	8:00 PM	0.41	0.53	0.34	0.93
5:00 PM	11:00 PM	0.91	8.670E-06***	0.91	8.670E-06***

Regarding backward waiting times, the empirical CDFs are shown to be higher than the reference CDFs for 6:00 a.m. and 2:30 p.m., and conversely, lower for 1:00 p.m. and 11:00 p.m. There is either insignificance or inconsistency among the data sets for the rest of the timings.

Supporting empirical evidences found from the mean tests are shown in Table 5.4. For forward waiting times, the empirical means of news arriving at 6:00 a.m. and 2:30 p.m. (8:00 p.m. and 11:00 p.m.) are statistically larger (smaller) than the mean of the reference waiting time sample. For backward waiting times, only 2:30 p.m. and 11:00 p.m. show significance. The empirical mean for backward waiting times for 2:30 p.m. is statistically smaller than its reference mean, while the relationship is converse for announcements arriving at 11:00 p.m.

Table 5.5 presents the p-values of the K-S test for comparing the empirical and reference CDFs of waiting times to jumps in the Swedish market. The purpose is to find the impact on the Swedish market of the arrivals of U.S. macroeconomic announcements at eight typical timings. The macroeconomic announcements at the following timings in CEST statistically have higher empirical CDFs than their reference counterparts for forward waiting times: 1:00 p.m., 3:45 p.m., and 11:00 p.m., while the announcements coming at 6:00 a.m. and 3:00 p.m. generate relatively lower empirical CDFs than the reference one.

Table 5.4: Means of Waiting Times with Macro News Arrival on Significant Timings (U.S. EDT) for Finnish large-cap data. The results are based on all data announcements and the filtered data set 1 (No other announcements within 6 h on both sides.) that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data)

Panel A **Forward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\bar{d}$	**Mean of** $\bar{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1529	40.75	15290	37.96	0.99	9.646E-03**
7:00 AM	1:00 PM	5692	40.67	56920	40.96	0.27	0.72
8:30 AM	2:30 PM	14918	40.57	149180	40.00	0.95	4.281E-02*
9:00 AM	3:00 PM	2244	40.35	22440	39.80	0.61	0.38
9:45 AM	3:45 PM	1458	38.92	14580	39.02	0.39	0.60
10:00 AM	4:00 PM	15525	39.24	155250	38.81	0.89	0.10
2:00 PM	8:00 PM	2097	36.72	20970	38.21	6.590E-02	0.93
5:00 PM	11:00 PM	5698	36.55	56980	37.49	4.116E-02*	0.95
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1413	39.96	14130	37.65	0.95	4.784E-02*
7:00 AM	1:00 PM	5605	40.55	56050	41.16	0.10	0.89
8:30 AM	2:30 PM	493	46.31	4930	39.38	0.99	2.965E-04***
9:00 AM	3:00 PM	2244	40.35	22440	39.80	0.61	0.38
9:45 AM	3:45 PM	1458	38.92	14580	39.02	0.39	0.60
10:00 AM	4:00 PM	2320	37.29	23200	39.01	4.988E-02*	0.95
2:00 PM	8:00 PM	1867	3600	18670	3776	6.695E-02	0.93
5:00 PM	11:00 PM	5698	36.55	56980	37.49	4.116E-02*	0.95

Panel B **Backward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\bar{d}$	**Mean of** $\bar{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1529	43.72	15290	43.99	0.32	0.67
7:00 AM	1:00 PM	5692	40.47	56920	40.23	0.66	0.33
8:30 AM	2:30 PM	14918	40.91	149180	41.59	1.890E-02*	0.98
9:00 AM	3:00 PM	2244	41.95	22440	41.79	0.49	0.50
9:45 AM	3:45 PM	1458	41.20	14580	42.23	0.17	0.82
10:00 AM	4:00 PM	15525	43.00	155250	42.88	0.59	0.40
2:00 PM	8:00 PM	2097	45.64	20970	46.01	0.34	0.65
5:00 PM	11:00 PM	5698	50.26	56980	49.10	0.97	2.510E-02*
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1413	42.11	14130	43.27	0.11	0.88
7:00 AM	1:00 PM	5605	40.23	56050	40.29	0.49	0.50
8:30 AM	2:30 PM	493	46.38	4930	40.89	0.99	2.557E-03**
9:00 AM	3:00 PM	2244	41.95	22440	41.79	0.49	0.50
9:45 AM	3:45 PM	1458	41.20	14580	42.23	0.17	0.82
10:00 AM	4:00 PM	2320	40.92	23200	43.02	6.343E-03**	0.99
2:00 PM	8:00 PM	1867	45.85	18670	46.46	0.23	0.76
5:00 PM	11:00 PM	5698	50.26	56980	49.10	0.97	2.510E-02*

For backward waiting times, the empirical CDFs are higher than the reference CDFs for 6:00 a.m., 2:30 p.m., and 3:00 p.m., and conversely, lower for 11:00 p.m. The rest of the timings are either insignificant or inconsistent among different data sets.

The results of the mean tests in Table 5.6 give empirical evidence supporting the K-S tests. For forward waiting times, the empirical means of news arriving at 6:00 a.m. and 3:00 p.m. (3:45 p.m.) are statistically larger (smaller) than the mean of the reference waiting time sample. For backward waiting times, only 4:00 p.m. and 11:00 p.m. show significance in different data sets.

The K-S test results for the impact of arrivals of U.S. macroeconomic announcements

Table 5.5: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Macro News Arrive at Significant Timings (U.S. EDT) on Swedish Markets. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides

Panel A: Forward Distances

		a) All Data		c) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
EDT	**CEST**				
12:00 AM	6:00 AM	0.80	5.724E-03**	0.52	1.955E-02*
7:00 AM	1:00 PM	1.703E-03**	0.86	2.000E-04***	0.89
8:30 AM	2:30 PM	0.12	5.307E-02	0.87	0.14
9:00 AM	3:00 PM	0.91	3.157E-03**	0.91	3.157E-03**
9:45 AM	3:45 PM	2.115E-05***	0.98	2.115E-05***	0.98
10:00 AM	4:00 PM	0.11	0.20	5.974E-02	0.52
2:00 PM	8:00 PM	8.569E-02	0.73	9.133E-02	0.28
5:00 PM	11:00 PM	1.070E-04***	0.92	1.070E-04***	0.92

Panel B: Backward Distances

		a) All Data		c) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
EDT	**CEST**				
12:00 AM	6:00 AM	5.487E-06***	0.29	3.908E-06***	0.79
7:00 AM	1:00 PM	0.31	2.977E-02*	0.28	6.733E-02
8:30 AM	2:30 PM	3.359E-06***	0.93	0.14	3.012E-02*
9:00 AM	3:00 PM	4.336E-02*	0.67	4.336E-02*	0.67
9:45 AM	3:45 PM	0.23	8.344E-02	0.23	8.344E-02
10:00 AM	4:00 PM	0.98	6.143E-03**	1.418E-02*	0.47
2:00 PM	8:00 PM	0.72	0.65	0.22	0.27
5:00 PM	11:00 PM	0.59	6.278E-04***	0.59	6.278E-04***

on the Danish market at eight typical timings, in the sense of waiting time to jumps, are shown in Table 5.7. The macroeconomic announcements at the following timings in CEST are shown to have higher empirical CDFs than their reference counterparts for forward waiting times: 1:00 p.m., 3:00 p.m., 3:45 p.m., and 11:00 p.m., while the announcements released at 4:00 p.m. generate relatively lower empirical CDFs than the reference one. Concerning backward waiting times, the empirical CDFs are shown to be lower than the reference CDF only for 11:00 p.m. It is either insignificant or inconsistent among different data sets for the rest of the timings. Empirical support is found from the mean tests, as shown in Table 5.8. For forward waiting times, the empirical means of news arriving at 3:00 p.m. and 4:45 p.m. are statistically smaller than the mean of the reference waiting time sample. For backward waiting times, no consistent significant results are found among the two data sets.

Table 5.6: Means of Waiting Times with Macro News Arrival on Significant Timings (U.S. EDT) for Swedish large-cap data. The results are based on all data announcements and the filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data)

Panel A **Forward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\bar{d}$	**Mean of** $\bar{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1484	36.73	14840	33.10	0.99	1.186E-03**
7:00 AM	1:00 PM	5561	36.63	55610	37.02	0.22	0.77
8:30 AM	2:30 PM	14545	35.89	145450	35.77	0.68	0.31
9:00 AM	3:00 PM	2182	36.91	21820	35.22	0.97	2.880E-02*
9:45 AM	3:45 PM	1427	32.01	14270	34.32	6.463E-03**	0.99
10:00 AM	4:00 PM	15138	34.93	151380	34.45	0.89	0.10
2:00 PM	8:00 PM	2059	33.10	20590	33.54	0.31	0.68
5:00 PM	11:00 PM	5545	32.70	55450	33.37	8.414E-02	0.91
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1372	34.89	13720	33.39	0.92	78E-02
7:00 AM	1:00 PM	5477	36.46	54770	37.06	0.10	0.89
8:30 AM	2:30 PM	476	38.87	4760	36.20	0.84	0.15
9:00 AM	3:00 PM	2182	36.91	21820	35.22	0.97	2.880E-02*
9:45 AM	3:45 PM	1427	32.01	14270	34.32	6.463E-03**	0.99
10:00 AM	4:00 PM	2289	33.51	22890	34.50	0.12	0.87
2:00 PM	8:00 PM	1835	33.20	18350	33.75	0.26	0.73
5:00 PM	11:00 PM	5545	32.70	55450	33.37	8.414E-02	0.91

Panel B **Backward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\bar{d}$	**Mean of** $\bar{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1484	39.10	14840	39.65	0.20	0.79
7:00 AM	1:00 PM	5561	36.24	55610	36.28	0.47	0.52
8:30 AM	2:30 PM	14545	37.31	145450	37.76	7.036E-02	0.92
9:00 AM	3:00 PM	2182	37.82	21820	37.87	0.37	0.62
9:45 AM	3:45 PM	1427	38.15	14270	38.65	0.46	0.53
10:00 AM	4:00 PM	15138	39.09	151380	38.51	0.96	3.106E-02*
2:00 PM	8:00 PM	2059	42.29	20590	42.01	0.56	0.43
5:00 PM	11:00 PM	5545	45.45	55450	45.00	0.82	0.17
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1372	38.46	13720	40.00	4.678E-02*	0.95
7:00 AM	1:00 PM	5477	36.24	54770	36.33	0.40	0.59
8:30 AM	2:30 PM	476	37.68	4760	37.46	0.73	0.26
9:00 AM	3:00 PM	2182	37.82	21820	37.87	0.37	0.62
9:45 AM	3:45 PM	1427	38.15	14270	38.65	0.46	0.53
10:00 AM	4:00 PM	2289	37.37	22890	38.31	0.17	0.82
2:00 PM	8:00 PM	1835	41.68	18350	41.69	0.58	0.41
5:00 PM	11:00 PM	5545	45.45	55450	45.00	0.82	0.17

Table 5.7: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for Macro News Arrive at Significant Timings (U.S. EDT) on Danish Markets. Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with generated data. Simulations are based on N iterations, where N is the number of announcements. Panels A and B report the forward distances and the backward distances. The results are based on all announcements and filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides

Panel A: Forward Distances

		a) All Data		c) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
EDT	**CEST**				
12:00 AM	6:00 AM	0.56	0.34	0.31	0.62
7:00 AM	1:00 PM	5.445E-05***	0.78	1.953E-05***	0.57
8:30 AM	1:00 PM	0.32	0.32	0.74	0.11
9:00 AM	3:00 PM	1.113E-02*	0.98	1.113E-02*	0.91
9:45 AM	3:45 PM	1.313E-02*	0.99	1.313E-02*	0.99
10:00 AM	4:00 PM	0.43	0.23	0.36	1.496E-02*
2:00 PM	8:00 PM	0.25	0.65	0.29	0.61
5:00 PM	11:00 PM	4.964E-05***	0.85	4.964E-05***	0.85

Panel B: Backward Distances

		a) All Data		c) Filtered Data Set 1. No other announcements within 6 h on both sides	
		h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
U.S. EDT	**CEST**				
12:00 AM	6:00 AM	0.14	0.95	4.876E-02*	0.82
7:00 AM	1:00 PM	0.18	9.551E-02	0.11	0.13
8:30 AM	2:30 PM	3.926E-03**	0.76	0.46	0.29
9:00 AM	3:00 PM	0.18	0.17	0.18	0.17
9:45 AM	3:45 PM	0.64	0.63	0.64	0.63
10:00 AM	4:00 PM	0.87	0.31	1.843E-05***	0.95
2:00 PM	8:00 PM	0.31	0.76	0.15	0.98
5:00 PM	11:00 PM	0.41	6.119E-03**	0.41	6.119E-03**

5.1.3 Concluding Remarks

If we take an overview of the test results among the three Nordic markets, we may conclude that the macroeconomic information arriving at 1:00 p.m., 3:45 p.m., and 11:00 p.m. CEST consistently affects the Nordic stock markets in terms of jumps. However, the morning (6:00 a.m.) macro announcements basically have no significant effect on Swedish and Danish stock prices. From the p-values of the K-S test at 2:30 p.m. for backward waiting times, Nordic stock prices possibly jump before announcements made at this moment. This might be due to the morning effect, since it is 8:30 a.m. in EDT. Furthermore, the Welch U mean tests support the empirical findings from the K-S tests.

Obviously, different markets react to the selected essential U.S. macroeconomic announcement timings in different ways. From the statistical significance point of view, the Finnish market is the most sensitive one to U.S. macro announcements. One possible explanation is that the large capital companies investigated in this research consist of a majority of global businesses. Thus, U.S. announcements may influence the export business of these companies. There are also certain propositions of stockholders who are foreign investors. They might balance their trading among international markets and make investment decisions partially on the basis of U.S. macroeconomic releases. Observably, small and

Table 5.8: Means of Waiting Times with Macro News Arrival on Significant Timings (U.S. EDT) for Danish large-cap data. The results are based on all data announcements and the filtered data set 1 that excludes announcements that had another announcement in the neighborhood of 6 hours on both sides. # Obs represents the number of observations. The Welch U-test p left tail and Welch U-test p right tail are the left and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Panel A **Forward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1100	28.10	11000	27.11	0.71	0.28
7:00 AM	1:00 PM	3996	30.05	39960	30.65	8.694E-02	0.91
8:30 AM	2:30 PM	10296	29.17	102960	29.21	0.42	0.57
9:00 AM	3:00 PM	1559	27.50	15590	28.89	2.824E-02*	0.97
9:45 AM	3:45 PM	979	26.70	9790	28.48	2.499E-02*	0.97
10:00 AM	4:00 PM	10804	28.22	108040	27.77	0.92	7.912E-02
2:00 PM	8:00 PM	1453	27.18	14530	27.11	0.42	0.57
5:00 PM	11:00 PM	4002	26.97	40020	27.60	8.776E-02	0.91
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1020	27.68	10200	27.70	0.39	0.60
7:00 AM	1:00 PM	3936	30.03	39360	30.45	0.14	0.85
8:30 AM	2:30 PM	320	29.71	3200	28.67	0.82	0.17
9:00 AM	3:00 PM	1559	27.50	15590	28.89	2.824E-02*	0.97
9:45 AM	3:45 PM	979	26.70	9790	28.48	2.499E-02*	0.9.750
10:00 AM	4:00 PM	1573	27.27	15730	28.00	0.27	0.72
2:00 PM	8:00 PM	1293	26.76	12930	26.73	0.41	0.58
5:00 PM	11:00 PM	4002	26.97	40020	27.60	8.776E-02	0.91

Panel B **Backward Distances** **a) All Data**		**#Obs of** d	**Mean of** d	**#Obs of** $\tilde{d}$	**Mean of** $\tilde{d}$	**Welch U-test p left tail**	**Welch U-test p right tail**
EDT	**CEST**						
12:00 AM	6:00 AM	1100	32.08	11000	33.12	0.11	0.88
7:00 AM	1:00 PM	3996	30.20	39960	29.83	0.75	0.24
8:30 AM	2:30 PM	10296	30.93	102960	31.18	0.17	0.82
9:00 AM	3:00 PM	1559	32.19	15590	31.27	0.86	0.13
9:45 AM	3:45 PM	979	31.73	9790	31.82	0.40	0.59
10:00 AM	4:00 PM	10804	32.67	108040	32.27	0.88	0.11
2:00 PM	8:00 PM	1453	34.49	14530	35.56	0.14	0.85
5:00 PM	11:00 PM	4002	39.43	40020	38.64	0.94	5.698E-02
b) Filtered Data Set 1							
EDT	**CEST**						
12:00 AM	6:00 AM	1020	31.89	10200	32.53	0.17	0.82
7:00 AM	1:00 PM	3936	30.27	39360	30.02	0.64	0.35
8:30 AM	2:30 PM	320	34.19	3200	31.53	0.86	0.13
9:00 AM	3:00 PM	1559	32.19	15590	31.27	0.86	0.13
9:45 AM	3:45 PM	979	31.73	9790	31.82	0.40	0.59
10:00 AM	4:00 PM	1573	29.93	15730	32.02	2.369E-03**	0.99
2:00 PM	8:00 PM	1293	34.65	12930	35.82	0.12	0.87
5:00 PM	11:00 PM	4002	39.43	40020	38.64	0.94	5.698E-02

open economies, such as Finland, Sweden, and Denmark, have one common, important export destination, which is the United States. Changes in the U.S. macro economy cause Nordic large capital companies' stock prices to fluctuate with a common pattern. As Eun and Shim (1989) stated, "innovations in the U.S. are rapidly transmitted to other markets in a clearly recognizable fashion, whereas no single foreign market can significantly explain the U.S. market movements." Mathur and Subrahmanyam (1990) tested the Granger's causality of Nordic market indices conditioning on U.S. indices and found that the U.S. market significantly influences Denmark, but not other Nordic countries. This evidence was found 20 years ago. Changes have been occurring due to the export trading policies of Nordic countries, which have been increasingly opening up. Recently, Omrane and Hussain (2016) provided empirical evidence of the significant impact of U.S. macroeconomic announcements on DAX 30 and CAC 40 volatilities from the German and French equity markets, respectively.

Conclusively, the impact of U.S. macroeconomic releases on Nordic stock prices is considerable. In particular, each market reacts to special timings due to the regularity of this U.S. macroeconomic information. Finally, it might be valuable for Nordic investors to note the empirical findings of this thesis, especially jumps of stock prices located close to 1:00 p.m., 3:45 p.m., and 11:00 p.m. CEST. This intraday pattern of Nordic equities is formed by the regular timings of U.S. macroeconomic announcements. Risk-averse investors may avoid trading at these three sensitive moments; whereas, risk lovers might implement their strategies around these jump times. Certain profits would be gained as long as the signs of jumps are correctly predicted in a relatively long horizon.

5.2 Application of U.S. News Announcements on U.S. Index

Macroeconomic announcements play an important role in financial markets. On the one hand, the releases of macroeconomic information affect various asset prices. Gilder et al. (2014) investigated the co-jumps among individual stocks and market portfolio in U.S. market. They documented that co-jumps are associated with the arrival of macroeconomic news, such as Federal Funds Target Rate announcements. Regarding the influence of U.S. macro news on exchange markets, Chatrath et al. (2014) found that 9 − 15 % of jumps in currency were directly related to U.S. announcements. Recently, El Ouadghiri et al. (2016) focused on the impact of macro news on Treasury bond returns. They found evidence that the bond market reacts to macro news releases, especially negative surprises. However, the surprises are not described by jumps. On the other hand, the volatility of financial products has also empirically been found to significantly react to the arrival of macro news. Andersen and Bollerslev (1998) investigated the intraday pattern of volatility in foreign exchange markets and showed that extremal returns are associated with the release of certain macroeconomic announcements. De Goeij and Marquering (2006) also provided empirical evidence that macro announcements strongly surprise the dynamics of bond market volatility.

To the best of my knowledge, the existing literature showing the impact of macro announcements on asset prices either adopts the classical event study methodology (El Ouadghiri et al., 2016) or applies regression on intraday factors (Andersen et al., 2003). However, one valuable viewpoint on the relationship between macroeconomic announcements and market reaction is the temporal character of news-related large changes in asset prices. Analyzing the waiting times between the arrivals of macro news and jumps in prices provides a straightforward way to uncover the temporal impact of

macroeconomic announcements on the reaction of the market, which is modeled as jumps in asset prices.

This section investigates the impact of U.S. macro announcements on the domesticin the statistical framework of waiting times. For the U.S. market, the temporal relationship between jumps in the S&P500 Index (SPY), for which ETFs are traded between 9:30 a.m. and 4:00 p.m., and U.S. macro announcements is analyzed via tests on waiting times. The U.S. macroeconomic announcements between January 2001 and December 2013 are from the Bloomberg World Economic Calendar. I select and focus on the following typical macro announcements: ADP Employment Change, CPI Core Index SA, Change in Nonfarm Payrolls, Chicago Purchasing Manager, FOMC Rate Decision (Upper Bound), Factory Orders, Initial Jobless Claims, Nonfarm Productivity, and the Underemployment Rate. S&P500 Index jumps are detected using the mid-prices of the SPY prices with millisecond precision timestamps. For Nordic markets, I first analyze the impact of aggregated macroeconomic announcements including 133 types of macro announcements for the purpose of testing the general impact of U.S. macro news on Finnish, Swedish, and Danish large capital equities. Then I focus on typical announcement times for U.S. macro news. Macro news is classified according to the announcement timestamps. The impacts of news with the same arrival clock times on Nordic equities is presented. The reason for focusing on announcement times is that there are strong overlaps of different macro announcements—that is, multiple macro news alerts arriving at the same time. Hence, a detected jump can hardly be concluded as relating to some certain macro news.

5.2.1 Impact of U.S. Macroeconomic Announcements on the U.S. Market

The empirical results in this section are from Kanniainen and Yue (2017) and implemented by Prof. Juho Kanniainen.

Table 5.9: Two-sample Kolmogorov-Smirnov, one-sided hypothesis test for *macro announcements with SPY* data: Testing whether the empirical and randomly generated distances come from populations with the same distribution against the alternative hypothesis that the cumulative distribution function of the distances with the empirical data is larger or smaller than that with the generated data. Rejection of the null hypothesis would indicate that the probability of having a jump detected before or after an announcement within a given time-interval is abnormally high or low, meaning that the observed time distances between the real announcements and the detected jumps are abnormally small or large compared with the distances between the generated time stamps and the detected jumps. Simulations are based on N iterations, where N is the number of announcements.

	Forward distances		Backward Distances	
Announcement	h_a: larger	h_a: smaller	h_a: larger	h_a: smaller
ADP Employment Change	0.017*	1.000	0.097	0.990
CPI Core Index SA	9.64E-03**	0.955	0.077	1.000
Change in Nonfarm Payrolls	5.93E-03**	0.879	0.993	0.044*
Chicago Purchasing Manager	0.089	0.676	0.439	0.018*
FOMC Rate Decision (Upper Bound)	3.19E-06***	0.973	0.977	0.046*
Factory Orders	0.086	0.929	0.204	0.386
Initial Jobless Claims	0.581	0.897	0.772	0.710
Nonfarm Productivity	0.262	0.597	0.204	0.249
Underemployment Rate	0.012*	1.000	0.102	0.989

Table 5.9 presents the p-values of the two-sample K-S test on the association between macro announcements and jumps in SPY in terms of backward and forward distances.

Table 5.10: Medians and means of the forward distances for the macro data sample."Bootstr. p left tail" and "Bootstr. p right tail" are the left- and right-tailed p-values calculated with the bootstrapping method, respectively, and the "Welch U-test p left tail" and "Welch U-test p right tail" are the left- and right-tailed p-values for the mean values calculated with the Welch U-test (unequal variances t-test for ranked data), respectively.

Forward Distances

Announcement	Mean of d^+	Mean of $\tilde{d}^+$	Bootstr. p left tail	Welch U-test p left tail	Bootstr. p right tail	Welch U-test p right tail
ADP Employment Change	37.878	55.275	1.80E-03**	5.90E-04***	0.998	0.999
CPI Core Index SA	40.315	55.282	6.30E-03**	3.74E-03**	0.994	0.996
Change in Nonfarm Payrolls	49.572	55.279	0.116	0.040*	0.884	0.960
Chicago Purchasing Manager	53.608	60.534	0.072	0.046*	0.928	0.954
FOMC Rate Decision	45.150	56.674	0.016*	6.18E-04***	0.984	0.999
Factory Orders	56.959	60.383	0.240	0.177	0.760	0.823
Initial Jobless Claims	53.994	55.274	0.295	0.267	0.706	0.733
Nonfarm Productivity	53.381	55.269	0.385	0.400	0.615	0.600
Underemployment Rate	28.054	55.291	2.10E-03**	8.67E-04***	0.998	0.999

Backward Distances

Announcement	Mean of d^-	Mean of $\tilde{d}^-$	Bootstr. p left tail	Welch U-test p left tail	Bootstr. p right tail	Welch U-test p right tail
ADP Employment Change	50.252	60.608	0.044*	0.031*	0.956	0.969
CPI Core Index SA	47.574	60.617	0.014*	0.011*	0.986	0.989
Change in Nonfarm Payrolls	66.198	60.683	0.868	0.903	0.132	0.097
Chicago Purchasing Manager	60.121	55.374	0.833	0.892	0.167	0.108
FOMC Rate Decision	67.152	59.092	0.915	0.972	0.085	0.028*
Factory Orders	56.896	55.493	0.624	0.530	0.376	0.470
Initial Jobless Claims	60.778	60.719	0.518	0.558	0.482	0.442
Nonfarm Productivity	63.926	60.649	0.719	0.663	0.281	0.337
Underemployment Rate	39.176	60.533	0.019*	0.011*	0.981	0.989

Two alternative hypotheses regarding the position of CDFs are considered: (i) The CDF with empirical announcements is larger than the reference CDF, which is labeled "h_a: larger" and (ii) the CDF with empirical announcements is smaller than the reference CDF, which is labeled "h_a: smaller." Jump detection is based on Lee and Mykland (2008) with a 1% significance level. For a smooth empirical distribution, only kernel density estimation is applied to FOMC Rate Decision for its various announcement times. As in the previous section, the number of observations in the reference sample is set to equal the squared number of observations in the K-S test sample. Moreover, Table 5.10 reports the bootstrap (10,000 iterations) and Welch U-test p-values for the means of the forward and backward waiting times, including right- and left-tailed values.

The results for forward distances indicate that ADP Employment Change, FOMC Rate Decision, and Underemployment Rate have consistently significant p-values in both the K-S and mean tests. These three macro announcement releases are statistically associated with forward jumps. In particular, FOMC announcements is shown to be the most influential announcement, which is in line with the findings of Hussain (2011); Lee (2012). Regarding backwards distances, no consistent significance in p-values is found among K-S and mean test results for the selected macro announcements apart from FOMC. This is not surprising, as almost all macro announcements are open information and mostly scheduled. Macro information can hardly be leaked shocking equity prices. However, FOMC announcements, whose announcement time cannot be exactly predictable, normally contain important news on monetary policy; therefore, stock markets could react before meetings in terms of abnormal returns or jumps. This empirical finding supports Lucca and Moench (2015).

5.2.2 Concluding Remarks

The impact of domestic announcements on U.S. index S&P 500 in terms of jumps is studied in this section. I select nine types of important U.S. macroeconomic news announcements reflecting four main characters of U.S. macro-economy, namely consumption, production, unemployment and monetary policy. The releases of monetary policy (FOMC) is found to be the most statistically associated to forward jumps in stock markets. News on unemployment also relates to forward jumps detected in S&P 500. This shows a channel how labor market impacts stock market. Consumption releases, e.g. CPI core index also contributes to forward jumps. However, no significant evidence is found from our sample showing a direct relation between news on production and jumps. Moreover, backward jumps are hardly linked to the selected macro announcements mainly due to they are public and scheduled.

6 News Events and Variance

How can we capture macroeconomic news arrivals in volatility modeling? Can the famous GARCH models capture the arrival of past and future macroeconomic news events in terms of model fitting and the performance of option valuation? The aim of this chapter is to answer these questions in the frame of GARCH models.

Macroeconomic news plays an important role in economic prediction. It is one of the most important types of public economic information utilized by investors. As a result of investors' trading, macroeconomic announcements impact asset prices. Andersen et al. (2003) found that U.S. macroeconomic announcements tend to produce jumps in the conditional mean of exchange rates and affect variances gradually as well. Chan (2003) investigated returns of individual companies following public news and found empirically that there are strong drifts in stock returns after the delivery of bad news. Intriguingly, important individual macro announcements are related to stock returns with great significance. Boyd et al. (2005) showed that a rising unemployment rate may trigger a large positive return with a large probability during an economic expansion period and vice versa. Lucca and Moench (2015) documented that the scheduled Federal Open Market Committee (FOMC) meetings always introduce large excess returns to the market during pre-meeting periods.

Asset returns generally reflect various information including macroeconomic news events. However, there is only some finance literature that explicitly jointly models return and macroeconomic variables. Engle and Rangel (2008) and Engle et al. (2013) introduced a Spline-GARCH model incorporating macroeconomic information directly. The dynamics of variance are driven by both past variance and some macroeconomic variables. However, there appears to be very little research on the impact of macroeconomic news on risk-neutral variance. In terms of asset pricing, I attempt to measure the impacts of macroeconomic fundamentals, especially scheduled macroeconomic announcements, on volatility under Q measure in order to investigate the option valuation performance. To explicitly model news in classical GARCH models, this work is strongly inspired by Engle and Rangel (2008) and Amado and Teräsvirta (2013). I extend the classical GARCH models to contain a news-impact multiplier. Given the predetermined schedule of macroeconomic news, I obtain a concise risk-neutral form for the GARCH model with news impact variable, which implies an analytical VIX formula. As a benefit of this design, the model also nests the classical GARCH models. In this thesis, I name the new model News-GARCH.

Option valuation in the frame of GARCH models started with the seminal work of Duan (1995), who specified a pricing kernel as a "locally risk neutral valuation relationship." Thereafter, Peter Christoffersen did a series of extensions, such as Christoffersen and Jacobs (2004), Christoffersen et al. (2008), Christoffersen et al. (2009), and Christoffersen

et al. (2012). One widely adopted model in the GARCH option pricing literature was introduced by Heston and Nandi (2000). I select the Heston-Nandi model, an affine GARCH model, as the benchmark. I also investigate the news impact on GJR-GARCH and NGARCH models.

From the empirical analysis, I find that adding the impact variables of the macroeconomic news arrivals to classical GARCH models helps to improve the model fitting with a slight magnitude. The performance of option pricing using the Heston-Nandi model can be consistently improved by considering the macroeconomic schedules. However, there are no such consistent results for NGARCH and GJR models. This shows that standard non-affine GARCH models without using news events data are sufficient for modeling the real macroeconomic news impacts from the viewpoint of option valuation.

This research relates to previous literature in many aspects, including model construction and estimation, with the following features distinguishing this thesis from prior work. First, I incorporate macroeconomic news impact variables in the transition function in Amado and Teräsvirta (2013). For the selection of news impact variables, instead of directly using the values of some macroeconomic variables, I only apply scheduled timings. For instance, I construct a new dummy variable on date t if there is news announced on that day. There are two obvious advantages of considering only the announcement moments. One is that all such variables in a certain time horizon are determined due to schedules, and they play as constants in the model; the other one is that the units of impact are unified among different news, and it is different from Engle and Rangel (2008). Second, Dorion (2013) recently introduced macro variables into the GARCH model for option valuation. The author used the ADS index as a state variable and modeled it as an autoregressive process. This setting ensures that the model implied VIX formula is not analytical or extremely complex. Additionally, the news impact in my model is relatively easy to test. Third, I implement MLE with the joint likelihood of market returns and VIX other than option prices. This aligns with Kanniainen et al. (2014) with the benefit of a small computational cost for model estimation. More econometric discussion on MLE and QMLE can be found in (Martin et al., 2012)

6.1 GARCH Model with Macroeconomic News Events

In this section, the Heston-Nandi GARCH(1,1) model is first presented. This model is widely applied in the discrete time option valuation literature; see Christoffersen et al. (2008) and Kanniainen et al. (2014). The Heston-Nandi GARCH(1,1) model serves as the benchmark model throughout this chapter I also investigate NGARCH and GJR models for the purpose of revealing the differences between affine and non-affine models for market data fitting and option valuation. I then extend all selected classical GARCH models to incorporate macroeconomic news information. Different measurements of the impact of macroeconomic news arrivals on variance are constructed. A risk-neutral form GARCH model with macroeconomic news is also presented.

6.1.1 Three Classical GARCH Models

6.1.1.1 The Heston and Nandi GARCH(1,1) Model

In line with the Heston stochastic volatility model in Heston (1993), Heston and Nandi (2000) proposed a GARCH model for return R_{t+1} and conditional variance h_{t+1} with an

analytical solution for the price of European options. The model is given as follows:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda h_{t+1} + \sqrt{h_{t+1}}\epsilon_{t+1} \tag{6.1}$$

$$h_{t+1} = \beta_0 + \beta_1 h_t + \beta_2\big(\epsilon_t - \beta_3\sqrt{h_t}\big)^2, \tag{6.2}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. Additionally, weak stationarity requires $\beta_1 + \beta_2\beta_3^2 < 1$.

6.1.1.2 NGARCH(1,1)

Engle and Ng (1993) provided strong empirical evidence of asymmetry in the impact of innovation on variance. As a result, the nonlinear GARCH model was introduced and was subsequently widely applied in the finance literature. The NGARCH model is as follows:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda\sqrt{h_{t+1}} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\epsilon_{t+1} \tag{6.3}$$

$$h_{t+1} = \beta_0 + h_t\big[\beta_1 + \beta_2(\epsilon_t - \beta_3)^2\big], \tag{6.4}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. Additionally, weak stationarity requires $\beta_1 + \beta_2(1 + \beta_3^2) < 1$.

6.1.1.3 GJR-GARCH(1,1)

Another popular benchmark model for variance asymmetry is the GJR model, which was first introduced by Glosten et al. (1993). In the model, negative innovation is designed to have a larger impact on variance than positive innovation.

The model is given as follows:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda\sqrt{h_{t+1}} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\epsilon_{t+1} \tag{6.5}$$

$$h_{t+1} = \beta_0 + h_t\big[\beta_1 + \beta_2\epsilon_t^2 + \beta_3\max(0, -\epsilon_t)^2\big], \tag{6.6}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. Additionally, weak stationarity requires $\beta_1 + \beta_2 + \beta_3/2 < 1$.

6.1.2 Return Dynamics with News Impact Variable

In the spirit of Engle and Rangel (2008), I sufficiently consider the macroeconomic impact on variance dynamics. I provide a new specification of the variance equation to incorporate news impact in the Heston-Nandi, NGARCH, and GJR models.

6.1.2.1 Multiplicative Time-varying News-H-N-GARCH(1,1)

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda\sigma_{t+1}^2 + \sigma_{t+1}\epsilon_{t+1} \tag{6.7}$$

$$\sigma_{t+1}^2 = (1+\gamma x_{t+1})[\beta_0 + \beta_1 h_t + \beta_2(\epsilon_t - \beta_3\sqrt{h_t})^2], \tag{6.8}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2\big(\epsilon_{t-1} - \beta_3\sqrt{h_{t-1}}\big)^2, \tag{6.9}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. x_t is the news impact measured on day t. γ is constant. It is easy to see that this specification nests the Heston-Nandi GARCH(1,1) when γ is 0.

6.1.2.2 Multiplicative Time-varying News-NGARCH(1,1)

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda\sigma_{t+1} - \frac{1}{2}\sigma_{t+1}^2 + \sigma_{t+1}\epsilon_{t+1} \tag{6.10}$$

$$\sigma_{t+1}^2 = (1+\gamma x_{t+1})[\beta_0 + \beta_1 h_t + \beta_2 h_t(\epsilon_t - \beta_3)^2], \tag{6.11}$$

$$h_t = \beta_0 + h_{t-1}\big[\beta_1 + \beta_2(\epsilon_{t-1} - \beta_3)^2\big], \tag{6.12}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. x_t is the news impact measured on day t. γ is constant. It is easy to see that this specification nests the NGARCH(1,1) model when γ is 0.

6.1.2.3 Multiplicative Time-varying News-GJR-GARCH(1,1)

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r + \lambda\sigma_{t+1} - \frac{1}{2}\sigma_{t+1}^2 + \sigma_{t+1}\epsilon_{t+1} \tag{6.13}$$

$$\sigma_{t+1}^2 = (1+\gamma x_{t+1})[\beta_0 + \beta_1 h_t + \beta_2 h_t\epsilon_t^2 + h_t\max(0,-\epsilon_t)^2], \tag{6.14}$$

$$h_t = \beta_0 + h_{t-1}\big[\beta_1 + \beta_2\epsilon_{t-1}^2 + \beta_3\max(0,-\epsilon_{t-1})^2\big], \tag{6.15}$$

where ϵ_t is a standard normal innovation, r is risk-free rate, and λ is the price of variance risk measuring the sensitivity of the change in conditional expected return with respect to conditional variance. $\beta_0 > 0$, $\beta_1,\ \beta_2 \geq 0$. x_t is the news impact measured on day t. γ is constant. It is easy to see that this specification nests the GJR-GARCH(1,1) model when γ is 0.

6.1.3 Modeling Impact of Macroeconomic News Events in Variance Dynamics

In this section, the news impact variable x_t is specified from U.S. macroeconomic releases.

6.1.3.1 Scheduled Macroeconomic Announcements

The schedulability of macroeconomic announcements is a significant property of the publication of macroeconomic information. Most important macroeconomic announcements, such as FOMC, are scheduled in one year. Their announcement timings are published in presses, such as world economic calendar[1]. To my knowledge, there has been little

[1] https://www.bloomberg.com/markets/economic-calendar

research investigating how the knowledge of forthcoming macroeconomic news affects traditional variance models and whether option valuation performance using classical models can be improved if such knowledge is sufficiently considered. To jointly model the announcements of macroeconomic news and asset returns, I first need to measure the impact of the arrival of macroeconomic information.

6.1.3.2 Individual News Indicator

I select 10 important news events of macroeconomic fundamentals from Bloomberg U.S. Economic Calendar. The individual news measurement I first consider is simply the dummy variable of news timestamps. For instance, let x_t denote the dummy impact of some news on day t. It takes the value of 1 if there is such a news announcement on day t, otherwise 0. These naive impacts only relate to the timing of news arrivals without other economic information.

$$
\begin{array}{c}
 \\ 29.01.2001 \\ 30.01.2001 \\ 31.01.2001 \\ 01.02.2001 \\ \dots \\ \dots \\ \dots \\ \\ \\ 05.01.2009
\end{array}
\begin{array}{c}
\begin{array}{cccccccc} FOMC & CPI & PPI & GDP & \dots & \dots & \dots & Umemployment\ Rate \end{array} \\
\begin{bmatrix}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \\
0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
 & & & & & & & \\
 & & & & & & & \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1
\end{bmatrix}
\end{array}
$$

6.1.3.3 Measurement from Dummy Regression

In this section, I construct two aggregate measures for the impacts of all selected 10 macroeconomic news items on variance via the dummy regression of realized variance and its increments on macroeconomic news indicators. Realized variance is widely known as a consistent estimator of daily variance using intraday prices; see Chapter 3 in Aït-Sahalia and Hansen (2009). To obtain a good approximation to daily conditional variance in the News-GARCH model, I predict the daily variance on the basis of the timing of macroeconomic announcements. I select $y_{1,t} = 1 - \frac{RV_t}{\overline{RV_{t,1:k}}}$, and $y_{2,t} = RV_t$ as the two dependent variables, where $\overline{RV_{t,1:k}}$ is the mean over realized variance $RV_{t-k}, ..., RV_{t-1}$ ($k = 5$ in the empirical analysis of this research). I regress $y_{i,t},\ i = 1, 2$ on the announcement timing dummy variables. In order to investigate the effect of near past and near future announcement arrivals on current variance, I also include the lag and forward dummy variables.

$$
\begin{aligned}
y_{i,t} =& \alpha_0 + \alpha_{1,-l}\mathbb{1}_{t-l}(CPI) + ... + \alpha_{1,0}\mathbb{1}_t(CPI) + ... + \alpha_{1,l}\mathbb{1}_{t+l}(CPI) \\
&+ \alpha_{2,-l}\mathbb{1}_{t-l}(PPI) + ... + \alpha_{2,0}\mathbb{1}_t(PPI) + ... + \alpha_{2,l}\mathbb{1}_{t+l}(PPI) \\
&\dots\dots\dots\dots\dots \\
&+ \alpha_{10,-l}\mathbb{1}_{t-l}(Con.Credit) + ... + \alpha_{10,0}\mathbb{1}_t(Con.Credit) + ... + \alpha_{10,l}\mathbb{1}_{t+l}(Con.Credit) \\
&+ \epsilon_t,\ i = 1, 2
\end{aligned}
\tag{6.16}
$$

Therefore, the corresponding impact variables are defined as dummy regression predictors $x_{1,t} = \hat{y}_{1,t}$ and $x_{2,t} = \frac{\hat{y}_{2,t}}{\alpha_0} - 1$.

The two news impacts $x_{1,t}$ and $x_{2,t}$ summarize the predicted relative increments of realized variance from all selected macroeconomic announcement dummy variables. Additionally, the model specification E.q. 6.9 motivates the selection of relative increments of realized variance instead of realized variance itself.

Generally, the news impact variable $1 + \gamma x_t$ in Equations 6.7, 6.10 and 6.13 could be negative and pragmatic for modeling variance. However, the news impact variables in this study are either indicators or predictors extracting from dummy regression of realized variance or increments of realized variance on news dummies. This implies that $x_{1,t}$ and $x_{2,t}$ are nonnegative or at least bounded from below. In the numerical optimization, I added a constraint such that $1 + \gamma x_{i,t},\ i = 1, 2$ is always positive. Other functional form of news impact function such as $\exp(1 + \gamma x_t)$ could be applied in future for robust analysis given that there is reasonable economic explanation for parameter γ.

6.1.4 Risk-Neutralization Dynamics

6.1.4.1 The Heston and Nandi GARCH(1,1) Model

For Heston-Nandi, the risk neutral form is the following:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\epsilon^*_{t+1} \tag{6.17}$$

$$h_{t+1} = \beta_0 + \beta_1 h_t + \beta_2(\epsilon^*_t - \tilde{\beta}_3\sqrt{h_t})^2 \tag{6.18}$$

where $\epsilon^*_t = \epsilon_t + \lambda$ and $\tilde{\beta}_3 = \beta_3 + \lambda + \frac{1}{2}$, is a standard normal innovation under a risk-neutral measure.

For News-Heston-Nandi, we have the following risk-neutral form:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}\sigma^2_{t+1} + \sigma_{t+1}\epsilon^*_{t+1} \tag{6.19}$$

$$\sigma^2_{t+1} = (1 + \gamma x_t)\big[\beta_0 + \beta_1 h_t + \beta_2(\epsilon^*_t - \tilde{\beta}_3\sqrt{h_t})^2\big] \tag{6.20}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2(\epsilon^*_{t-1} - \tilde{\beta}_3\sqrt{h_{t-1}})^2 \tag{6.21}$$

where $\epsilon^*_t = \epsilon_t + \lambda$ and $\tilde{\beta}_3 = \beta_3 + \lambda + \frac{1}{2}$, is a standard normal innovation under a risk-neutral measure.

6.1.4.2 The NGARCH(1,1) Model

For the NGARCH model, the risk neutral form is the following:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\epsilon^*_{t+1} \tag{6.22}$$

$$h_{t+1} = \beta_0 + h_t\big[\beta_1 + \beta_2(\epsilon^*_t - \tilde{\beta}_3)^2\big] \tag{6.23}$$

where ϵ^*_t is a standard normal innovation under risk-neutral measure and $\tilde{\beta}_3 = \beta_3 + \lambda$.

For News-NGARCH, we have the following risk-neutral form

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}\sigma_{t+1}^2 + \sigma_{t+1}\epsilon_{t+1}^* \tag{6.24}$$

$$\sigma_{t+1}^2 = (1+\gamma x_{t+1})[\beta_0 + h_t\beta_1 + \beta_2 h_t(\epsilon_t^* - \tilde{\beta}_3)^2] \tag{6.25}$$

$$h_t = \beta_0 + h_{t-1}\big[\beta_1 + \beta_2(\epsilon_{t-1}^* - \tilde{\beta}_3)^2\big] \tag{6.26}$$

where ϵ_t^* is a standard normal innovation under risk-neutral measure and $\tilde{\beta}_3 = \beta_3 + \lambda$.

6.1.4.3 The GJR model

For the GJR mdoel, the risk neutral form is the following:

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\epsilon_{t+1}^* \tag{6.27}$$

$$h_{t+1} = \beta_0 + h_t\big[\beta_1 + \beta_2(\epsilon_t^* - \lambda)^2 + \beta_3\max(0, -\epsilon_t^* + \lambda)^2\big] \tag{6.28}$$

where ϵ_t^* is a standard normal innovation under risk-neutral measure.

For News-GJR, we have the following risk-neutral form

$$\ln(S_{t+1}/S_t) \equiv R_{t+1} = r - \frac{1}{2}\sigma_{t+1}^2 + \sigma_{t+1}\epsilon_{t+1}^* \tag{6.29}$$

$$\sigma_{t+1}^2 = (1+\gamma x_{t+1})[\beta_0 + \beta_1 h_t + \beta_2 h_t(\epsilon_t^* - \lambda)^2 + \beta_3\max(0, -\epsilon_t^* + \lambda)^2] \tag{6.30}$$

$$h_t = \beta_0 + h_{t-1}\big[\beta_1 + \beta_2(\epsilon_{t-1}^* - \lambda)^2 + \beta_3\max(0, -\epsilon_{t-1}^* + \lambda)^2\big] \tag{6.31}$$

where ϵ_t^* is a standard normal innovation under risk-neutral measure.

6.1.5 VIX Implied from News-GARCH models

VIX is an index measuring the forthcoming one month conditional risk-neutral variance. It was first proposed in 1993 by the Chicago Broad Option Exchange(CBOE). The calculation is simply based on weighted average of At-the-Monety implied volatilities on S&P 100 options using Black-Scholes formula. The maturity of VIX is 30 calendar days. The new VIX was developed in 2003. The At-the-Monety S&P 100 option prices used in calculation were replaced by Out-of-the-Monety S&P 500 option prices.

The annualized VIX formula[2] implied from News-GARCH model is the following

$$\mathbf{VIX}_t^{Model}(\tau) = 100\Big(\frac{252}{\tau}\mathbf{E}_t^Q\big[\sum_{k=1}^{\tau}(1+\gamma x_{t+k})h_{t+k}\big]\Big)^{1/2} \tag{6.32}$$

$$= 100\Big(\frac{252}{\tau}\sum_{k=1}^{\tau}(1+\gamma x_{t+k})\mathbf{E}_t^Q[h_{t+k}]\Big)^{1/2} \tag{6.33}$$

$$= 100\Big(\frac{252}{\tau}\sum_{k=1}^{\tau}(1+\gamma x_{t+k})\big(\sigma^2 + (h_{t+1} - \sigma^2)\tilde{b}^{k-1}\big)\Big)^{1/2}, \quad \tau \geq 1 \tag{6.34}$$

[2]The derivative of VIX formula here is similar to the classical GARCH models discussed in Kanniainen et al. (2014).

where $\tilde{b} = \beta_1 + \beta_2 \tilde{\beta_3}^2$ for News-Heston-Nandi GARCH, $\tilde{b} = \beta_1 + \beta_2(1 + \tilde{\beta_3}^2)$ for News-NGARCH model, and $\tilde{b} = \beta_1 + [\beta_2 + \beta_3 N(\lambda)](1 + \lambda^2) + \beta_3 \lambda n(\lambda)$ for News-GJR GARCH model (For more details, see Duan et al. (2006b)). $N(\cdot)$ and $n(\cdot)$ denote the standard normal distribution and density functions respectively. $\sigma^2 = \frac{\beta_0 + \mathbb{1}_{HN}\beta_2}{1-\tilde{b}}$, where $\mathbb{1}_{HN}$ is the indicator function valued 1 for Heston-Nandi, for other models it is zero. x_t denotes the news impact variable. $\tau = 30$ is the time to maturity.

6.2 Daily Return and VIX Empirics

6.2.1 Data Description

The empirical work in this chapter is based on the following macroeconomic news data, VIX index, S&P 500 index, and its European options from the U.S. market.

6.2.1.1 Macroeconomic Announcements

I collect 10 types of U.S. macroeconomic announcements from Bloomberg World Economic Calendar. These 10 announcements include *CPI*(Consumer Confidence Index), *PPI*(Producer Price Index), *ABC*(ABC Consumer Confidence Index), *ADP*(ADP Employment Change), *Change Payrolls*(Change in Nonfarm Payrolls), *FOMC*(Federal Open Market Committee Meeting), *Factory Orders*, *Productivity*(Nonfarm Productivity), *Real Earnings*, and *Consumer Credit* in the U.S. market from January 2001 to December 2011. The data are structured with date and time at one-minute precision, announced value, and market forecast value. There are two reasons to select these 10 typical announcements. On the one hand, selected news events should reflect important economic factors such as consuming, produce and employment; on the other hand, I focus on the U.S. macroeconomic announcements whose sample size is acceptably large for a good model estimation.

6.2.1.2 Returns and Realized Variance

I choose the S&P 500 index with different sampling frequencies from December 31, 2000 to December 31, 2009 as the underlying asset in this work. For log returns, I use daily closing prices. To calculate daily realized variance, I use 5-min S&P 500 index.

6.2.1.3 Option Data

I select S&P 500 call and put options from January 3, 2001 to December 31, 2009. To filter the option data, I follow the method in Bakshi et al. (1997). In particular, quotes were filtered out if the prices are less than \$ 3/8 or the standard no-arbitrage conditions were not satisfied. Moreover, options with maturities longer than 365 calendar days were removed as well. For the sake of liquidity, the options whose daily volume are less than 100 were dropped. Finally, only the Wednesday options data are used due to weak day-of-the-week effects.

Table 6.1 provides the statistics for options data by moneyness and maturity. Panel A reports the number of option contracts I adopt. Panel B presents the mean option prices for different moneyness and days to maturities. From panel C, I observe clearly the implied volatility smile with short DTM (Days to Maturity), and smirk with long DTM.

Table 6.1: S&P 500 Index Option Data Jan 2001 - Dec 2009 I use European call and put options on the S&P 500 index. The prices are taken from quotes on each Wednesday from January 03, 2001 to December 31, 2009. The moneyness and maturity filters from Bakshi et al. (1997) are applied here. The implied volatilities are calculated using the Black-Scholes formula. DTM refers to the number of days to maturity and S/K refers to moneyness defined as the underlying index level divided by the option strike price.

Moneyness	$DTM < 60$	$60 < DTM < 80$	$80 < DTM < 180$	$180 < DTM$	All
Panel A. Number of option contracts					
$S/K < 0.975$	7320	999	2846	2177	13342
$0.975 < S/K < 1.00$	5384	649	1487	884	8404
$1.00 < S/K < 1.025$	5127	549	1308	855	7839
$1.025 < S/K < 1.05$	3195	286	844	494	4819
$1.05 < S/K < 1.075$	2388	244	647	344	3623
$1.075 < S/K$	7109	950	3065	2217	13341
All	30523	3677	10197	6971	51368
Panel B. Average option price					
$S/K < 0.975$	18.65	28.89	29.01	47.27	26.30
$0.975 < S/K < 1.00$	21.26	37.26	47.66	74.35	32.75
$1.00 < S/K < 1.025$	22.06	37.28	47.33	71.93	32.78
$1.025 < S/K < 1.05$	18.23	30.03	39.97	60.21	27.04
$1.05 < S/K < 1.075$	15.08	23.97	32.77	54.74	22.60
$1.075 < S/K$	11.47	16.99	20.35	29.93	16.97
All	17.69	28.31	32.62	49.50	26.41
Panel C. Average implied volatility from options					
$S/K < 0.975$	0.23	0.22	0.20	0.19	0.22
$0.975 < S/K < 1.00$	0.18	0.19	0.19	0.19	0.18
$1.00 < S/K < 1.025$	0.19	0.20	0.21	0.20	0.20
$1.025 < S/K < 1.05$	0.22	0.20	0.21	0.20	0.21
$1.05 < S/K < 1.075$	0.24	0.23	0.23	0.21	0.23
$1.075 < S/K$	0.36	0.33	0.30	0.26	0.33
All	0.24	0.24	0.23	0.22	0.23

6.2.2 Joint Estimation using Returns and VIX

VIX as a risk-neutral information source has been used widely to estimate asset pricing models. For example, for continuous models, Duan and Yeh (2010) estimated a stochastic volatility model with jumps using VIX data. Regarding GARCH models calibration, Kanniainen et al. (2014) estimated three GARCH models with VIX and improved the model performance for option valuation. Hao and Zhang (2013) considered five GARCH models and concluded that the GARCH implied VIX based on return data is systemically lower than VIX[3]. In this section, I concisely demonstrate a general joint likelihood function for the GARCH model using both returns and VIX data.

The joint likelihood function consists of two sub-likelihood functions. One is of the innovation in return equation and the other part is of the error between model-free (Market) VIX and GARCH implied VIX.

$$\ln L = \ln L(\epsilon^R; \Theta) + \ln L(\epsilon^{VIX}; \Theta') \tag{6.35}$$

$$\epsilon^R_{t+1} = \frac{R_{t+1} - \mathbb{E}_t(R_{t+1})}{\sqrt{h_{t+1}}}, \tag{6.36}$$

where ϵ^R_t is IID random variable with zero mean and unit variance, while ϵ^{VIX} is a zero mean normal vector whose dimension is as same as term structure vector. Θ and Θ' are parameters. In this chapter, the VIX term structure error is defined as

$$\epsilon^{VIX}_t = \mathbf{VIX}_t - \mathbf{VIX}^{Model}_t, \tag{6.37}$$

where $\mathbf{VIX}_t$ are model-free VIX market data extracted from option prices at t, $\mathbf{VIX}^{Model}_t$ is the corresponding model implied VIX estimates. In the empirical analysis, the 30-day VIX is applied and the error series between market and model implied VIX can be assumed independent, or allowed to be autocorrelated. I allow the autocorrelation in ϵ^{VIX}_t and specify the vector series as a VAR(1) process.

$$\epsilon^{VIX}_t = \Psi \epsilon^{VIX}_{t-1} + e^{VIX}_t, \tag{6.38}$$

where e_t is a standard normal vector. Ψ is a diagonal matrix controlling the autocorrelation for the VIX error series at each term. Under this setting, the joint likelihood functions is given by

$$\ln L = \ln L(\epsilon^R; \Theta) + \ln L(\epsilon^{VIX}; \Theta') \tag{6.39}$$

$$= -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{n}\left\{\ln h_t - \frac{\big(R_t - \mathbb{E}_t(R_t)\big)^2}{h_t}\right\} \tag{6.40}$$

$$- \frac{nT}{2}\ln(2\pi) - \frac{n-1}{2}\ln|\Sigma - \Psi\Sigma\Psi'| - \frac{1}{2}\sum_{t=2}^{n} e^{VIX\prime}_t(\Sigma - \Psi\Sigma\Psi')^{-1}e^{VIX}_t, \tag{6.41}$$

where Σ is the contemporaneous variance of ϵ^{VIX}_t, and n is the sample size. For more details on maximum likelihood estimation with autocorrelated error, see Beach and MacKinnon (1979).

[3]This might be due to the inconsistent means of counting days in $[t, T]$—namely, from spot time to maturity. The authors used 252 days for a year, but 30 days for a month in their paper.

Table 6.2: Joint Return and VIX MLE Estimates for Heston-Nandi News GARCH I use daily return and VIX from Jan 02, 2001 to Dec 31, 2009 to estimate Heston-Nandi(*H-N*) and News-GARCH(1,1) models with different news impact measurements. Ten important individual macroeconomic news are selected: *CPI*(consumer confidence index), *PPI*(producer price index), *ABC*(ABC Consumer Confidence Index), *ADP*(ADP Employment Change), *Change Payrolls*(Change in Nonfarm Payrolls), *FOMC*(Federal Open Market Committee Meeting), *Factory Orders*, *Productivity*(Nonfarm Productivity), *Real Earnings*, and *Consumer Credit* in U.S. market. The measurement x_t of all individual news is simply an indicator variable. I also introduce variables for the mixed news impact taking advantage of dummy regression of realized variance on the selected macroeconomic announcement timing indicators. This mixed measurement is denoted by $x_{1,t}$ and $x_{2,t}$, and l is the local time window of selected macro news dummies same as in 6.1.3.3. They are the predicted value of the increment of variance based on macroeconomic announcement dummy times, which reveals the aggregate news impact on variance. $\log \mathcal{L}$ denotes log likelihood. Estimated standard errors are reported in parentheses.

	$\log \mathcal{L}$	β_0	β_1	β_2	β_3	λ	ρ	γ
No News	6.184	1.616E-06	0.618	2.594E-06	3.654E+02	2.491	0.984	-
	-	(1.374E-07)	(1.850E-02)	(1.553E-07)	(20.190)	(1.563)	(4.368E-04)	-
CPI	6.185	1.617E-06	0.616	2.601E-06	3.660E+02	2.487	0.984	1.080E-02
	-	(1.376E-07)	(1.874E-02)	(1.585E-07)	(20.46)	(1.563)	(4.428E-04)	(6.345E-03)
PPI	6.185	1.590E-06	0.615	2.619E-06	3.679E+02	2.341E-11	0.984	-4.554E-03
	-	(1.371E-07)	(1.824E-02)	(1.533E-07)	(19.310)	(0.780)	(5.566E-04)	(1.131E-02)
ABC	6.189	9.431E-07	0.686	3.170E-06	3.013E+02	1.356E-03	0.981	-1.372E-02
	-	(1.209E-07)	(1.360E-02)	(1.832E-07)	(15.370)	(1.570)	(6.023E-04)	(3.804E-03)
ADP	6.191	8.794E-07	0.688	3.292E-06	2.930E+02	2.084E-02	0.981	4.802E-02
	-	(1.229E-07)	(1.364E-02)	(1.908E-07)	(15.20)	(1.570)	(6.004E-04)	(9.876E-03)
Payrolls	6.191	1.039E-06	0.670	3.140E-06	3.086E+02	2.157E-11	0.982	4.977E-02
	-	(1.272E-07)	(1.465E-02)	(1.796E-07)	(15.620)	(0.647)	(5.737E-04)	(9.990E-03)
FOMC	6.189	8.773E-07	0.690	3.261E-06	2.941E+02	4.681E-11	0.981	-5.613E-03
	-	(1.198E-07)	(1.342E-02)	(1.869E-07)	(14.760)	(0.871)	(5.726E-04)	(6.805E-03)
Factory Orders	6.189	8.745E-07	0.691	3.262E-06	2.935E+02	1.743E-02	0.981	3.671E-03
	-	(1.212E-07)	(1.349E-02)	(1.894E-07)	(15.210)	(1.576)	(5.924E-04	(1.067E-02
Productivity	6.189	8.791E-07	0.690	3.261E-06	2.940E+02	1.358E-02	0.981	-7.133E-03
	-	(1.193E-07)	(1.336E-02)	(1.881E-07)	(15.09)	(1.568)	(5.748E-04)	(1.277E-02)
Real Earnings	6.189	8.955E-07	0.688	3.258E-06	2.948E+02	1.529E-11	0.982	1.563E-02
	-	(1.234E-07)	(1.352E-02)	(1.841E-07)	(14.56)	(0.630)	(6.509E-04)	(1.553E-02)
Consumer Credit	6.190	8.764E-07	0.688	3.286E-06	2.933E+02	6.482E-02	0.981	1.806E-02
	-	(1.197E-07)	(1.335E-02)	(1.882E-07)	(14.980)	(1.569)	(5.682E-04)	(8.081E-03)
$x_{1,t},\ l=0$	6.189	8.784E-07	0.689	3.245E-06	2.957E+02	4.856E-13	0.981	-6.112E-03
	-	(1.201E-07)	(1.360E-02)	(1.813E-07)	(14.430)	(2.217)	(5.825E-04)	(9.620E-03)
$x_{2,t},\ l=0$	6.189	8.717E-07	0.692	3.280E-06	2.920E+02	2.177E-06	0.981	2.009E-02
	-	(1.212E-07	(1.339E-02)	(1.889E-07)	(14.960)	(1.569)	(5.852E-04)	(9.725E-03)
$x_{1,t},\ l=5$	6.189	8.770E-07	0.690	3.266E-06	2.939E+02	2.513E-09	0.981	-1.031E-03
	-	(1.202E-07)	(1.366E-02)	(1.889E-07)	(15.20)	(1.573)	(5.702E-04)	(8.650E-03)
$x_{2,t},\ l=5$	6.189	8.505E-07	0.692	3.272E-06	2.929E+02	5.154E-12	0.981	-5.195E-03
	-	(1.218E-07)	(1.323E-02)	(1.827E-07)	(14.280)	(1.915)	(5.777E-04)	(3.243E-03)

Table 6.2 presents parameter estimates and standard errors for the pure Heston-Nandi GARCH model and the Heston-Nandi with 14 impact variables of macroeconomic news. The log likelihoods of models with macroeconomic impacts are higher than the pure Heston-Nandi model. However, the improvement is relatively small. The most significant macroeconomic news which yield higher likelihood are ADP Employment Change, Change in Nonfarm Payrolls, and Consumer Credit.

The macroeconomic news impacts on variance can be read from the values of γ. The arrivals of CPI, ADP, Payrolls, Factor Orders, Real Earnings and Consumer Credit tend to enlarge the daily spot variance from Heston-Nandi GARCH, whereas PPI, ABC,

FOMC, Productivity and aggregated impacts shrink the spot variance from Heston-Nandi GARCH. The magnitude is smaller than 5%.

The estimated autocorrelation coefficient ρ is consistently larger than 0.98 for all specifications associated to Heston-Nandi GARCH. This phenomenon is also observed in Kanniainen et al. (2014), and this stems from the strong autocorrelated VIX index.

Parameter λ measures the relative risk aversion. There is a large difference in the estimated λ between the pure Heston-Nandi GARCH model and the News-Heston-Nandi model with 14 impact variables of macroeconomic news. For pure Heston-Nandi GARCH, $\lambda = 2.491$ shows a significantly positive risk premium. However, such property is only observed for CPI in the News-Heston Nandi GARCH model. Moreover, the λ in most specifications of News-Heston Nandi GARCH model lacks for statistical significance.

Table 6.3 provides parameter estimates and standard errors for the pure NGARCH model and the NGARCH with 14 impact variables of macroeconomic news. The log likelihoods of models with macroeconomic impacts are higher than the pure NGARCH model. However, the improvement is quite small. The most significant macroeconomic news which yield higher likelihood is Nonfarm Payrolls, and Consumer Credit.

The macroeconomic news impacts on variance can be read from the values of γ. The arrivals of CPI, ABC, ADP, Payrolls, FOMC, Factor Orders, and Consumer Credit tend to enlarge the daily spot variance from Heston-Nandi GARCH, whereas PPI, Productivity, Real Earnings and aggregated impacts shrink the spot variance from NGARCH. The magnitude is smaller than 3%. The estimated autocorrelation coefficient ρ is consistently larger than 0.96 for all specifications associated to NGARCH. Additionally, risk premium parameters λ in all specifications are valued near zero and statistically insignificant.

Table 6.4 reports the parameter estimates and standard errors for the pure GJR-GARCH model and the GJR-GARCH model with 14 impact variables of macroeconomic news. The log likelihoods of models with macroeconomic impact variables are higher than the pure GJR model. However, the improvement is small. The most significant macroeconomic news events yielding higher likelihood are Nonfarm Payrolls and ADP Employment Change.

The macroeconomic news impacts on variance can be read from the values of γ. The arrivals of ADP and Payrolls tend to enlarge the daily spot variance from the Heston-Nandi GARCH, whereas CPI, ABC, PPI, Productivity, Real Earnings, FOMC, Factor Orders, Consumer Credit, and aggregated impacts shrink the spot variance from NGARCH. The magnitude is smaller than 5%.

The estimated autocorrelation coefficient ρ is consistently larger than 0.93 for all specifications associated with the GJR-GARCH model. In contrast with Heston-Nandi and NGARCH model, the relative risk aversion parameter λ in GJR-GARCH model is statistically significant in each specification. The volatility risk premium is not negligible under the GJR-GARCH and News-GJR GARCH model.

A substantial empirical observation is that the NGARCH model outperforms the Heston-Nandi and GJR model with and without news impacts in terms of likelihoods. This finding was also confirmed by Kanniainen et al. (2014). Additionally, the slight improvements in likelihoods between NGARCH and News-NGARCH as well as GJR and News-GJR demonstrate non-affine GARCH models' ability for empirical data fitting.

Table 6.3: Joint Return and VIX MLE Estimates for NGARCH News GARCH I use daily return and VIX from Jan 02, 2001 to Dec 31, 2009 to estimate NGARCH and News-NGARCH(1,1) models with different news impact measurements. Ten important individual macroeconomic news are selected: *CPI*(consumer confidence index), *PPI*(producer price index), *ABC*(ABC Consumer Confidence Index), *ADP*(ADP Employment Change), *Change Payrolls*(Change in Nonfarm Payrolls), *FOMC*(Federal Open Market Committee Meeting), *Factory Orders*, *Productivity*(Nonfarm Productivity), *Real Earnings*, and *Consumer Credit* in U.S. market. The measurement x_t of all individual news is simply a indicator variable. I also introduce variables for the mixed news impact taking advantage of dummy regression of realized variance on the selected macroeconomic announcement timing indicators. This mixed measurement is denoted by $x_{1,t}$ and $x_{2,t}$, and l is the local time window of selected macro news dummies same as in 6.1.3.3. They are the predicted value of the increment of variance based on macroeconomic announcement dummy times, which reveals the aggregate news impact on variance. $\log \mathcal{L}$ denotes log likelihood. Estimated standard errors are reported in parentheses.

	$\log \mathcal{L}$	β_0	β_1	β_2	β_3	λ	ρ	γ
No News	6.412	1.292E-06	0.760	2.170E-02	3.120	1.794E-12	0.966	-
	-	(8.047E-08)	(4.643E-03)	(5.784E-04)	(7.622E-02)	(5.094E-03)	(5.779E-04)	-
CPI	6.412	1.293E-06	0.760	2.171E-02	3.121	6.673E-13	0.966	2.484E-03
	-	(7.772E-08)	(4.406E-03)	(5.696E-04)	(7.292E-02)	(1.025E-02)	(5.681E-04)	(5.555E-03)
PPI	6.412	1.292E-06	0.760	2.170E-02	3.120	4.786E-13	0.966	-1.657E-04
	-	(7.845E-08)	(4.635E-03)	(6.008E-04)	(7.659E-02)	(5.559E-03)	(5.751E-04)	(6.817E-03)
ABC	6.412	1.287E-06	0.760	2.169E-02	3.122	1.138E-15	0.966	1.251E-03
	-	(7.770E-08)	(4.547E-03)	(5.661E-04)	(7.264E-02)	(7.125E-02)	(6.264E-04)	(2.570E-03)
ADP	6.413	1.287E-06	0.759	2.177E-02	3.114	9.185E-13	0.966	2.375E-02
	-	(7.800E-08)	(5.039E-03)	(6.059E-04)	(7.770E-02)	(7.075E-03)	(5.668E-04)	(6.340E-03)
Payrolls	6.414	1.285E-06	0.759	2.175E-02	3.118	5.448E-14	0.966	2.451E-02
	-	(7.697E-08)	(5.185E-03)	(5.943E-04)	(8.071E-02)	(7.737E-03)	(6.530E-04)	(6.419E-03)
FOMC	6.412	1.293E-06	0.759	2.171E-02	3.122	3.469E-13	0.966	3.828E-03
	-	(7.753E-08)	(4.650E-03)	(5.854E-04)	(7.658E-02)	(5.982E-03)	(5.792E-04)	(3.992E-03)
Factory Orders	6.412	1.294E-06	0.759	2.174E-02	3.119	9.643E-13	0.966	5.499E-03
	-	(7.801E-08)	(4.433E-03)	(5.759E-04)	(7.613E-02)	(1.893E-02)	(5.759E-04)	(4.948E-03)
Productivity	6.412	1.292E-06	0.760	2.169E-02	3.121	4.154E-13	0.966	-4.020E-03
	-	(8.309E-08)	(4.395E-03)	(5.696E-04)	(7.357E-02)	(6.269E-03)	(5.740E-04)	(1.412E-02)
Real Earnings	6.412	1.262E-06	0.760	2.163E-02	3.125	2.078E-12	0.967	-1.966E-02
	-	(7.776E-08)	(4.411E-03)	(5.746E-04)	(7.329E-02)	(5.365E-03)	(6.140E-04)	(9.539E-03)
Consumer Credit	6.413	1.286E-06	0.7591	2.177E-02	3.114	2.591E-13	0.966	2.061E-02
	-	(7.791E-08)	(4.413E-03)	(5.691E-04)	(7.317E-02)	(8.527E-03)	(5.671E-04)	(6.054E-03)
$x_{1,t},\ l=0$	6.412	1.286E-06	0.760	2.182E-02	3.120	1.608E-14	0.967	1.242E-02
	-	(7.754E-08)	(4.770E-03)	(5.677E-04)	(7.254E-02)	(6.251E-02)	(5.753E-04)	(6.630E-03)
$x_{2,t},\ l=0$	6.412	1.297E-06	0.757	2.172E-02	3.120	8.926E-14	0.966	6.422E-03
	-	(8.513E-08)	(4.406E-03)	(5.763E-04)	(7.348E-02)	(9.329E-03)	(5.846E-04)	(5.720E-03)
$x_{1,t},\ l=5$	6.413	1.299E-06	0.762	2.177E-02	3.107	5.853E-13	0.966	-1.887E-02
	-	(8.149E-08)	(4.421E-03)	(5.815E-04)	(7.366E-02)	(6.010E-03)	(5.907E-04)	(5.083E-03)
$x_{2,t},\ l=5$	6.416	1.192E-06	0.764	2.153E-02	3.126	5.486E-15	0.969	-1.609E-02
	-	(7.369E-08)	(4.297E-03)	(5.700E-04)	(7.233E-02)	(5.234E-02)	(7.152E-04)	(2.271E-03)

Table 6.4: Joint Return and VIX MLE Estimates for GJR News GARCH I use daily return and VIX from Jan 02, 2001 to Dec 31, 2009 to estimate GJR-GARCH and News-GJR-GARCH(1,1) models with different news impact measurements. Ten important individual macroeconomic news are selected: *CPI*(consumer confidence index), *PPI*(producer price index), *ABC*(ABC Consumer Confidence Index), *ADP*(ADP Employment Change), *Change Payrolls*(Change in Nonfarm Payrolls), *FOMC*(Federal Open Market Committee Meeting), *Factory Orders*, *Productivity*(Nonfarm Productivity), *Real Earnings*, and *Consumer Credit* in U.S. market. The measurement x_t of all individual news is simply a indicator variable. I also introduce variables for the mixed news impact taking advantage of dummy regression of realized variance on the selected macroeconomic announcement timing indicators. This mixed measurement is denoted by $x_{1,t}$ and $x_{2,t}$, and l is the local time window of selected macro news dummies same as in 6.1.3.3. They are the predicted value of the increment of variance based on macroeconomic announcement dummy times, which reveals the aggregate news impact on variance. $\log \mathcal{L}$ denotes log likelihood. Estimated standard errors are reported in parentheses.

	$\log \mathcal{L}$	β_0	β_1	β_2	β_3	λ	ρ	γ
No News	6.147	1.195E-06	0.934	1.334E-17	8.763E-02	0.208	0.937	-
	-	(8.263E-08)	(1.190E-03)	(2.950E-02)	(1.553E-03)	(1.971E-02)	(1.220E-03)	-
CPI	6.148	1.379E-06	0.932	1.078E-17	8.992E-02	0.195	0.936	-2.143E-03
	-	(9.377E-08)	(1.227E-03)	(2.921E-02)	(1.598E-03)	(1.972E-02)	(9.845E-04)	(7.982E-03)
PPI	6.147	1.273E-06	0.934	1.383E-14	8.959E-02	0.190	0.936	-3.336E-03
	-	(8.792E-08)	(1.253E-03)	(5.785E-04)	(1.631E-03)	(1.967E-02)	(1.147E-03)	(7.380E-03)
ABC	6.149	1.432E-06	0.934	1.231E-15	8.963E-02	0.193	0.932	-1.478E-02
	-	(9.428E-08)	(1.256E-03)	(8.460E-03)	(1.621E-03)	(1.988E-02)	(1.014E-03)	(2.510E-03)
ADP	6.151	1.359E-06	0.931	5.279E-16	9.037E-02	0.194	0.936	4.095E-02
	-	(9.273E-08)	(1.221E-03)	(6.812E-03)	(1.591E-03)	(1.975E-02)	(9.890E-04)	(8.553E-03)
Payrolls	6.151	1.362E-06	0.931	1.285E-16	9.041E-02	0.194	0.936	4.081E-02
	-	(9.269E-08)	(1.222E-03)	(3.839E-03)	(1.591E-03)	(1.975E-02)	(9.860E-04)	(8.525E-03)
FOMC	6.148	1.377E-06	0.933	1.294E-16	8.974E-02	0.195	0.936	-6.652E-03
	-	(9.301E-08)	(1.233E-03)	(6.666E-03)	(1.596E-03)	(1.979E-02)	(9.771E-04)	(3.489E-03)
Factory Orders	6.148	1.377E-06	0.932	1.232E-17	8.987E-02	0.194	0.9359	-2.005E-03
	-	(9.326E-08)	(1.235E-03)	(3.205E-02)	(1.585E-03)	(1.978E-02)	(9.722E-04)	(7.648E-03)
Productivity	6.148	1.383E-06	0.933	3.568E-17	8.978E-02	0.194	0.936	-1.399E-02
	-	(9.363E-08)	(1.228E-03)	(8.517E-03)	(1.583E-03)	(1.981E-02)	(9.798E-04)	(8.977E-03)
Real Earnings	6.148	1.370E-06	0.932	4.090E-16	8.994E-02	0.195	0.937	-1.784E-02
	-	(9.281E-08)	(1.214E-03)	(1.207E-02)	(1.582E-03)	(1.970E-02)	(1.287E-03)	(2.220E-02)
Consumer Credit	6.147	1.384E-06	0.932	1.106E-10	8.991E-02	0.194	0.936	-1.703E-03
	-	(9.523E-08)	(1.376E-03)	(7.024E-04)	(1.675E-03)	(1.976E-02)	(1.050E-03)	(5.638E-03)
$x_{1,t},\ l=0$	6.148	1.388E-06	0.933	5.386E-17	8.958E-02	0.194	0.935	-7.237E-03
	-	(9.358E-08)	(1.516E-03)	(1.223E-02)	(1.675E-03)	(1.993E-02)	(9.735E-04)	(6.083E-03)
$x_{2,t},\ l=0$	6.148	1.385E-06	0.932	2.501E-17	9.001E-02	0.194	0.935	1.339E-02
	-	(9.354E-08)	(1.207E-03)	(2.541E-02)	(1.598E-03)	(1.977E-02	(9.783E-04	(5.189E-03
$x_{1,t},\ l=5$	6.149	1.408E-06	0.933	1.283E-16	8.985E-02	0.195	0.936	-2.896E-02
	-	(9.453E-08)	(1.230E-03)	(1.695E-02)	(1.579E-03)	(1.976E-02)	(9.607E-04)	(5.344E-03)
$x_{2,t},\ l=5$	6.149	1.364E-06	0.934	1.945E-17	8.978E-02	0.197	0.939	-1.414E-02
	-	(9.240E-08)	(1.230E-03)	(2.497E-02)	(1.578E-03)	(1.994E-02)	(1.154E-03)	(2.713E-03)

6.3 Option Valuation

In this section, I investigate the option valuation performance of the three GARCH models with and without macroeconomic news impacts. I apply Monte Carlo simulation to calculate model based prices. For each price, I generate 10000 paths.

6.3.1 Option Valuation Results

Table 6.5: Option Pricing Error $\mathcal{V}$RMSE This table summarizes the vega weighted root-mean-square error (RMSE) of option pricing errors. I consider all 15 specifications with and without news events. GARCH models include standard Heston-Nandi, News-Heston-Nandi GARCH model, NGARCH, News-NGARCH, GJR, and News-GJR. The estimates used in the pricing procedure extracted from joint MLE.

	Heston-Nandi	*NGARCH*	*GJR*
No News	4.081	3.250	3.621
CPI	4.074	3.249	3.627
PPI	4.074	3.251	3.624
ABC	4.014	3.246	3.648
Unemployment	4.047	3.244	3.665
Payrolls	4.043	3.237	3.658
FOMC	4.016	3.248	3.624
Factory Orders	4.017	3.249	3.626
Productivity	4.015	3.252	3.620
Real Earnings	4.024	3.243	3.622
Consumer Credit	4.030	3.242	3.628
$x_{1,t},\ l=0$	4.009	3.230	3.622
$x_{2,t},\ l=0$	4.024	3.251	3.631
$x_{1,t},\ l=5$	4.019	3.269	3.617
$x_{2,t},\ l=5$	4.017	3.275	3.627

Table 6.5 presents the vega weighted root-mean-square error (RMSE) of option pricing errors for Heston-Nandi, NGARCH and GJR GARCH models with and without macroeconomic news impacts. The vega weighted root-mean-square error $\mathcal{V}$RMSE is defined as

$$\mathcal{V}RMSE = 100 \times \sqrt{\frac{1}{N_M}\sum_{t,i}\left(\frac{O_{t,i}-\widehat{O}_{t,i}}{\widehat{\mathcal{V}}_{t,i}}\right)^2} \tag{6.42}$$

Here, $O_{t,i}$ is the model price of the ith option at time t, $\widehat{O}_{t,i}$ is the corresponding market price of the same option contract, $\widehat{\mathcal{V}}_{t,i}$ denotes (Black, 1976) vega (the derivative with respect to volatility) computed at the implied volatility using the true market prices of options. Formally,

$$\hat{\mathcal{V}}_{t,i} = \frac{\partial O_{t,i}}{\partial \widehat{\sigma}_{t,i}} = s_{t,i}\sqrt{T_{t,i}}n(d_1) \tag{6.43}$$

$$d_1 = \frac{\log(s_{t,i}/K_{t,i}) + (r + \widehat{\sigma}^2_{t,i}/2)t}{\widehat{\sigma}_{t,i}\sqrt{t}} \tag{6.44}$$

where $s_{t,i}$ is the underlying asset price of contract i at time t, $T_{t,i}$, $K_{t,i}$ and $\widehat{\sigma}_{t,i}$ are the corresponding maturity, strike price and implied volatility. r is the risk-free rate. $n(\cdot)$ denotes the density function of the standard normal random variable. Moreover,

$N_M = \sum_{t=1}^{M} N_t = 51368$ (see Table 6.1), where N_t denotes the number of option prices in the sample at time t, and M is the total number of days in the sample.

I observe the following option pricing empirics: First, the affine GARCH model (Heston-Nandi) with and without macroeconomic news impacts is of a larger option pricing error than its non-affine (NGARCH and GJR) counterparts. Second, the news impacts on Heston-Nandi improve option valuation performance consistently. Finally, for NGARCH and GJR, the delivery of macroeconomic information does not help for option valuation. The non-affine models successfully absorb macroeconomic impacts.

Table 6.6: Calibrated Parameters and Option Pricing Error This table summarizes the calibrated parameters and the vega weighted root-mean-square error (RMSE) of option pricing errors for the following six specifications: Heston-Nandi, News-Heston-Nandi GARCH model, NGARCH, News-NGARCH, GJR, and News-GJR. News impact variable $x_{2,t},\ l = 5$ is the same as 6.1.3.3.

	β_0	β_1	β_2	β_3	λ	γ	$\mathcal{V}$RMSE
Heston-Nandi	1.074E-27	0.297	2.245E-06	5.548E+02	-	-	3.642
$x_{2,t},\ l = 5$	1.074E-27	0.297	2.245E-06	5.548E+02	-	2.500E-04	3.642
NGARCH	9.241E-07	0.845	6.549E-02	1.159	-	-	3.170
$x_{2,t},\ l = 5$	9.241E-07	0.845	6.549E-02	1.159	-	6.875E-04	3.169
GJR	8.653E-07	0.901	8.517E-11	0.197	1.062E-05	-	3.190
$x_{2,t},\ l = 5$	8.653E-07	0.901	8.517E-11	0.197	1.062E-05	9.375E-04	3.190

As a robust check, I calibrate the three pure GARCH models and three News-GARCH models. The macroeconomic news impact selected in calibration is the aggregated impact variable $x_{2,t},\ l = 5$ is the same as 6.1.3.3. Table 6.6 reports the calibrated results. From the calibrated $\mathcal{V}$RMSE, I conclude that adding macroeconomic impacts hardly help GARCH models for option pricing. There are several possible reasons for this finding. First, specification of News-GARCH by multiplying a news impact variable might be not appropriate for pricing option. Second, the construction of news impact variable could influence the performance of option pricing. Third, numerical optimization might be inefficient. Finally, explicit modeling real news might be redundant for option valuation, because the information of macroeconomic news arrivals is in nature contained in return data.

6.4 Concluding Remarks

In this chapter, I extend three classical GARCH models, Heston-Nandi GARCH, NGARCH and GJR model, by explicitly introducing a variable of macroeconomic news arrival. The variable is constructed in two ways, one is as a dummy variable indicating single macroeconomic announcement arrival, and the other considers the impact of multiple arrivals of important macroeconomic releases on variance via dummy regression of realized variance on a bunch indicators for the arrivals of selected macroeconomic news. To investigate whether the classical GARCH models sufficiently capture the past and future arrivals of macroeconomic announcements, I compare the likelihood and the performance of option valuation between classical GARCH models and their counterparts with macroeconomic news events.

Joint MLE method is applied to estimating all GARCH models using both daily returns and VIX index. Using VIX data in the estimation for GARCH models at least has the following two advantages. First, the estimated models not only fit the return data but also capture

option prices. Second, it is computationally economical for directly using VIX index instead of option prices (Christoffersen et al., 2008), as the analytical formula of VIX implied from selected GARCH models exist in a concise form, more discussion see (Kanniainen et al., 2014). Moreover, the errors between market VIX and model implied VIX are assumed to follow an AR(1) process due to strong autocorrelation in VIX data. From the empirical results, I find that classical GARCH models capture macroeconomic information sufficiently, for explicitly incorporating the arrivals of macroeconomic announcements into GARCH models does not significantly improve the joint likelihood compared with classical GARCH models.

The same findings are also obtained from examining the performance of option valuation. Only affine GARCH models with news variable slightly outperform the Heston-Nandi GARCH model in pricing S&P 500 European options. However, there is no consistent results for NGARCH and GJR model. This implies that the effect of explicit macroeconomic releases on returns could be properly captured a nonlinear GARCH model.

Even though some estimates and specification of GARCH models with news are not statistically significant, the models are still considered to provide certain economic significance. In particular, the multiplier of news impact variable controls the scale of daily variance dynamics, which is crucial for the performance of option valuation. A small change of the multiplier would result into a complete behavior of GARCH models. Additionally, a good selection of nonlinear functional form of variance equation may lead to a better performance in model fitting and option pricing than directly including real news variable into classical GARCH models.

7 Discussion and Conclusions

7.1 Discussion

Financial markets develop rapidly in size and complexity mainly due to the increasing amount of news. A good understanding of financial and economic news is the key to perceiving markets and making wise investment decisions. However, owing to the vast amount and complexity of formats, it is impossible to examine all news that is useful to investors and that affects asset prices. In particular, most valuable news is in text format. This research provides several possibilities for measuring news quantitatively and incorporating news impact into classical financial models.

The non-parametric framework introduced to illustrate the impact of announcements on jumps in stock prices stands on two cornerstones. One is the jump detection method. Several jump detection methods have been developed in high-frequency financial econometrics. Generally, they can be divided into two classes according to the construction of the detection statistics. The first class e.g., (Barndorff-Nielsen and Shephard, 2004; Huang and Tauchen, 2005; Jiang and Oomen, 2008), mainly considers the difference between jump sensitive and robust volatility estimators. One disadvantage of these tests is that the jump detection window is relatively large due to the demand for an accurate estimator for integral variance. The large detection window leads to relatively imprecise jumping times. To overcome this, the second class of tests (Andersen and Bondarenko, 2007; Lee and Mykland, 2008) focuses on the ratio of log return and the corresponding spot volatility estimator. This design largely shrinks the jump detection window to the same as log return. In practice, the detection in (Lee and Mykland, 2008) provides accurate local windows with jumps for intraday stock prices.

The other cornerstone of the framework is simulating reference timestamps with intraday seasonal pattern. The procedure comprises two steps. First, the number of daily announcements is uniformly simulated among time horizon with the same sample size of real announcements. Second, a single announcement follows the empirical distribution of real announcements. The main goal is to obtain a sample of timestamps of "general news," which theoretically should not contribute to jumps. By no means is this simulation method unique, as long as the arrival of general news does not fluctuate markets in terms of jumps. This procedure mainly concerns the effect of intraday seasonal patterns in both announcements and jumps. The focus on waiting times differs this research from traditional event study on abnormal returns of individual stocks, more related analysis can be found in (Corrado, 2011; Kolari and Pynnönen, 2010; Kolari and Pynnonen, 2011).

Several empirical findings need to be discussed. First, the Finnish and Danish markets uniformly react to non-scheduled firm-specific announcements, whereas jumps in the Swedish market seems unrelated to the arrival of non-scheduled announcements. One

possible answer to this question is that investors in the Swedish stock market do not trade on non-scheduled announcements. Consequently, the arrivals of non-scheduled announcements do not immediately lead to a large change in Swedish stock prices. This finding was also partially confirmed by Metghalchi et al. (2008) in testing the efficiency of the Swedish stock market. They documented the significant power of technical trading rules in predicting Swedish stock prices. This finding illustrates that large stock returns might be mainly conditional on past prices and scheduled information, instead of unscheduled Swedish firm-specific news. A deep investigation into the textual contents of the announcements could be helpful; however, this is beyond the scope of this thesis.

Second, the abnormal statistical behavior of backward waiting times possibly indicates information leakage in Nordic markets. From the K-S and Welch U-tests for waiting time analysis with second nearest jumps, I found uniformly significant results among the three markets showing that Nordic stock prices react to non-scheduled announcements earlier than general simulated announcements.

Third, the sizes of jumps related to scheduled announcements were found to be generally larger than those of non-scheduled announcements in the Nordic markets. This also highlights the fact that investors trade more based on scheduled news. Furthermore, negative jumps were detected more frequently than positive ones in the sample period from 2006 to 2010, partly due to the financial crisis in 2008.

Fourth, concerning the impact of selected firm-specific announcements, I found that news on interim reports contributes greatly to jumps in the stock prices of Nordic large capital listed companies. This suggests the importance of interim reports to investors in Nordic markets. In event study literature, typical firm events, such as initial public offerings and mergers, have been documented relating abnormal returns, see (Bessembinder and Zhang, 2013). More recently, Kolari et al. (2015) revisited results from (Bessembinder and Zhang, 2013) and showed that alpha in the regression still partially represents abnormal returns of event firms and their controls. However, it is quite surprising that there is scarce literature discussing how investors gain valuable information from interim reports.

Fifth, the impact of U.S. macroeconomic releases on typical times was investigated. The reason why I focused on the announcement time is that most macroeconomic news is announced at a certain clock time. This strong overlap mixes up the effects of all macroeconomic news events at that moment. 1:00 p.m., 3:45 p.m., and 11:00 p.m. CEST are important clock times to Nordic investors, for a significant association with jumps was found for these moments. This stresses the importance of the arrival times of U.S. macroeconomic news.

Apart from the impact of U.S. macroeconomic releases on jumps, I studied the impact on variance. I incorporated the news variable into three popular GARCH models: Heston-Nandi GARCH, NGARCH, and GJR models. In particular, I priced S&P 500 European options using the extended GARCH models with news impact. In pricing options, the first challenge is that the risk-neutral pricing principle should not be violated by introducing news into classical GARCH models. In other words, the underlying asset with the news variable should still be specified as a martingale process under a risk-neutral measure, see (Bühlmann et al., 1998; Christoffersen et al., 2009). Instead of extracting the content of various macro releases, I focused on the announcement timestamps. Taking advantage of the fact that almost all important macroeconomic releases are scheduled normally one year in advance, I jointly modeled the predictable macroeconomic news flow and the return process in the frame of a GARCH model. In this way, the existing option pricing

techniques with GARCH models still work when sufficiently considering the arrival of macro announcements.

The single impact of a certain type of macro announcement is described by the indicator variable of announcement date. The composite impact of a set of macroeconomic releases is extracted from regression realized variance on the dummy variables of announcement times for macroeconomic announcements. Although only considering the announcement moments of macro releases leaves out important information in the text contents, having a predictable news process is beneficial. As a result, modeling VIX and pricing options with the news process is fairly easy to carry out. What is more, the construction of the news impact variable using macro announcement dates is by no means only as presented in this research.

In respect to the selection of GARCH models, I only considered three widely applied models in empirical asset pricing. It would be beneficial to examine other GARCH models (e.g., (Christoffersen et al., 2008)), in terms of market data fitting and option valuation performance.

7.2 Validity, Reliability, and Limitations

This section briefly answers the research questions that are addressed in the section 1.2 by discussing the validity (Did I answer right questions?), reliability (accuracy), and limitations of this research.

- *Is there a statistical association between jumps in stock prices and the arrivals of important news events in Nordic and U.S. markets?*

  This question can be answered by observing the significant differences in statistical behaviors of waiting times with the arrivals of real news compared to the simulated time stamps. For forward waiting times, the distribution of real news is empirically higher than the reference simulated ones. However, regarding backward waiting times, there is no such large difference between distributions and means founded for news events (i.e. non-scheduled announcements). The nonparametric tests applied in this research make the statistical framework widely applicable. The intraday seasonal pattern is sufficiently considered in the procedure of simulating reference sample of news events. Accordingly, the results from the empirical analysis are robust. It is worth noting that simulating the arriving timestamps of general news is by no means unique, and this might lead to different results with respect to different simulation designs for the reference sample. For example, one might capture intraweek or intramonth seasonal patterns that could be seen as a possible extension of this research. In terms of analyzing U.S. macroeconomic announcements, special attention should be paid to mixing effect, which is generated by multiple macroeconomic news events that arrive at the same time. It is difficult to identify the individual contribution of certain types of macro releases on jumps. Furthermore, this mixing effect leads to inefficient filtering for macro news events. For example, there could be confounding U.S. macro events that cannot be filtered out because otherwise there would be nothing left in the data sample.

- *How to measure the association between jumps in stock prices and the arrivals of news events?*

  Relying on the analysis of waiting times and the nonparametric statistical framework, the association between jumps in stock prices and the arrivals of news events is uncovered in the sense of market reaction speed. Waiting times only refer to the timestamps of selected news events and detected jumps, which are accurate due to reliable source of intraday high frequency data. However, in order to study the composite sample of news events, only common characteristics of various events, such as arriving timestamps, can be considered. The contents of different types of events, which are mostly in text format, have to be neglected. It might be possible to solve this problem better by using both traditional econometric techniques and advanced machine learning for text readings. Consequently, more information that is valuable can be extracted from various news sources and properly included in financial models.

- *Do firm-specific scheduled and nonscheduled announcements contribute to jumps in Nordic markets? If so, what characteristics of jump sizes that associate with announcements?*

  For Nordic scheduled and non-scheduled firm-level announcements, clear impacts of scheduled announcements on the post-announcement jump process across the Finnish, Swedish, and Danish markets have been found, whereas, non-scheduled announcements show an exception, which is the Stockholm exchange. The difference between distributions of real news and the general reference is insignificant. The results are reliable because the classification of scheduled news and non-scheduled news are clearly defined with well-specified filtering rules. Additionally, scheduled announcements are found to generate large jumps with a greater probability than non-scheduled announcements. Furthermore, negative jumps are found to be more common and have larger sizes than positive jumps. This finding is consistent with existing literature (e.g. (Lahaye et al., 2011)). The same empirical analysis can be applied to other datasets in order to investigate the the impact of firm-specific announcements on international markets in terms of jumps. Additionally, an alternative way to answer these two questions simultaneously is to extend the nonparametric statistical framework to two dimensions that include both waiting times and jump sizes. Accordingly, the K-S tests and Welch mean tests must be adjusted to two variables. This potential extension of the statistical method would be valuable to demonstrate the impact of news events on jumps from multiple points of view.

- *Does the Nordic market react to typical firm-level announcements, such as acquisitions and changes in board members, in terms of jumps in stock prices?*

  The selected firm-specific announcements were all tested statistically to contribute the following jumps in different extent. This contribution related to market reactions to jumps, which are measured by waiting times. It would be arbitrary to conclude

that there is a causal relationship between the arrivals of these firm-level announcements and jumps detected in the neighborhoods. The selection of the five specific types of firm-level announcements originates from the following considerations: the first is the economic importance of corporate finance, and the second is for the necessity to obtain a relatively large sample in order to have a good estimation of CDFs. However, the association of other types of announcements and jumps are easily investigated within the same nonparametric statistical framework according to personal interests.

- *How do U.S. macroeconomic announcements contribute to jumps in U.S. and Nordic markets?*

  Generally, the U.S. macroeconomic announcements are crucial to stock markets. The analysis in section 5.1 shows that U.S. macroeconomic releases are statistically associated with forthcoming jumps. This finding supports existing literature such as (Lee and Mykland, 2008). Compared to firm-specific news events, the impact of certain types of macroeconomic announcements is relatively difficult to address, because the announcing timings of many macroeconomic releases are strongly overlapping. Only a few typical macro announcements, such as FOMC, are tested clearly contributing to jumps. A similar conclusion is drawn in (Lucca and Moench, 2015) as well. To overcome the influence of this overlapping effects, I grouped the U.S. macro news events by the releasing clock times. Again, this manner focuses on the temporal property of macro releases instead of their contents. Therefore, the aim here is to analyze the different impact of macro news events that arrive at different clock times in terms of jumps in stock prices.

  The impacts of U.S. macro effects on Nordic markets are proved to be significant from the datasets. However, this investigation moves in a single direction. Therefore, it might be beneficial to examine the impacts that news events announcing in Nordic and other market have on the U.S. market.

- *How to incorporate macroeconomic news impact into GARCH models for option valuation?*

  First, the news impact variable is constructed in two ways. One is simply adopting the dummy variable of the arrivals of macro releases. The temporal impact of macro releases is recorded other than their nature. This makes it easier to compare the temporal effects of different macro news. One possible extension for a certain type of macro news is to directly use the values of this variable, such as GDP and CPI. An other way to model the impact of macro releases is to use the predictor from a regression of the increment realized variance on a set of important macro dummy variables. This could address the mixed effects of arriving macroeconomic events on realized variance. In these two ways, the impact of U.S. macro news is measured based on accurate arriving times. However, it is still not unique to model the impact of macro news on variance.

  To include these impact variables into GARCH models, I was inspired by the

work of Amado and Teräsvirta (2013), and made the classical GARCH models as a special case of the extended News-GARCH models. Consequently, the extended models with news variables are in a neat form and reliable in terms of statistical inference and option pricing.

- *Does macroeconomic information explicitly improve GARCH models for fitting market data?*

  Compared to classical GARCH models, the joint likelihood of corresponding News-GARCH models has not improved significantly. This could be due to the construction of the news impact variable, the way that the news variable is incorporated into classical GARCH models and the numerical optimization methods applied to MLE. This study does not answer this question generally, but rather provide answers under the given model specifications. Therefore, it is still unknown if there is a specification that could improve the model by using data on macro announcements. Finally, other specifications are worth investigating, aside from the three popular GARCH models discussed in this research.

- *Do standard GARCH models sufficiently capture the macro economic news events in terms of option valuation performance?*

  The option valuation performance of GARCH models with macro news variables is found not outperforming classical GARCH models consistently. This comparison is based on a reliable Monte Carlo simulation for option valuation. As discussed in the market data fitting, the minor contributions to the option valuation of macro news variables are probably due to the specifications of the News-GARCH models and macro news variable as well. Finally, option pricing performance could be improved through other potential specifications with macro news variables in the GARCH class.

7.3 Conclusions

Realizing the importance of financial and economic news to risk management and asset pricing, I investigated the impact of firm-specific and macroeconomic announcements on jumps and variance of stock prices in both Nordic and U.S. markets.

First, a non-parametric framework was designed to statistically reveal the impact of announcements on jumps in stock prices. The framework consists of detecting jumps, simulating timestamps of general reference announcements, collecting backward and forward waiting times, and statistically comparing empirical and reference waiting times. These procedures have been proven effective in empirical work, especially for analyzing the reaction speed of markets to the arrival of specific types of announcements in terms of jumps in stock prices. Additionally, studying the statistical behavior of back waiting times is helpful for explaining markets' pre-reactions, possibly induced by information leakage.

Second, in applying the statistical framework, I provided a detailed empirical analysis for Nordic firm-specific and U.S. macroeconomic announcements using high-frequency Nordic stock prices and SPY. For Nordic scheduled and non-scheduled firm-level announcements, I identified clear impacts of scheduled announcements on the post-announcement jump process across the Finnish, Swedish, and Danish markets. However, non-scheduled announcements were found to be related to jumps only in the Copenhagen and Helsinki exchange data, not in the Stockholm exchange data. Additionally, some evidence showed jumps distributed abnormally in equity prices preceding company announcements in the Finnish and Danish stock markets, possibly indicating information leakage. Furthermore, scheduled and non-scheduled announcements were found to have a continuous impact on Nordic markets in terms of (pre-)sequential jumps, and the second nearest jumps react weakly to delivered announcements compared to the first jumps.

The size of jumps associated with scheduled and non-scheduled announcements in Nordic markets was studied as well. I found that scheduled announcements contribute significantly to the likelihood of generating large jumps after announcements, while information leakage can hardly proceed through non-scheduled announcements in terms of jump sizes. Moreover, negative jumps dominate positive jumps in both amount and size.

Besides scheduled and non-scheduled announcements, I selected five typical classes of announcements and analyzed their impact on Nordic stock prices. The selected typical firm-specific announcements included acquisition, change in board composition, change in capital, company announcement, and interim report. The forward waiting times of acquisition were found to be longer than the average. Tests for changes to boards showed different levels of significance on the Nordic markets. News of changes in board composition tend to drive Finnish and Danish markets to be more volatile than the Swedish market. Among all selected announcements, I found that stock prices jump most actively and promptly after the release of interim reports in the three Nordic markets.

Third, I examined how U.S. macro announcements influence U.S. and Nordic stock prices. I observed a considerable impact from U.S. macroeconomic releases on Nordic stock prices. Releases about FOMC were found to contribute to generating jumps in SPY. Macroeconomic announcements arriving at 1:00 p.m., 3:45 p.m., and 11:00 p.m. CEST affect the Nordic stock markets significantly in terms of jumps.

Overall, I found strong evidence that jumps in stock prices can be driven by both past and forthcoming announcements. This empirical observation contributes to extending the existing jump models in risk management and option pricing.

Regarding the impact of U.S. macroeconomic announcements on variance, I investigated the effect of macroeconomic news delivery on three popular GARCH models: Heston-Nandi GARCH, NGARCH, and GJR models. In particular, the performance of option valuation for these GARCH models with and without macroeconomic information were compared to answer the question of whether classical GARCH models sufficiently capture past and future arrivals of macroeconomic announcements in terms of option pricing.

I first constructed the impact variables for certain important macroeconomic announcements. Instead of considering the content and values of these announcements, I only focused on the announcement timings, which are normally scheduled one year in advance. Taking advantage of the schedulability of macroeconomic announcements, the impact variables are predictable. I constructed a single news impact variable as the indicator of such news arrival. I also extracted the aggregated impact variable using dummy regression of realized variance on all selected macroeconomic announcements.

To incorporate news impact variables into the GARCH models, I viewed the impact variable as a multiplier on variance equation. Such a design illustrates that the spot variance is not only determined by historical spot variance and innovation but also by the arrival of current macroeconomic news. Moreover, I employed the joint MLE method to estimate all models using both daily returns and VIX index. I allowed the error series to follow an AR(1) process, which is a more realistic assumption than IID. I found that all models with macroeconomic news are of higher likelihood than their classical GARCH counterpart. However, the improvements of macroeconomic news delivery on likelihood are generally minor.

With estimates from return and VIX, I priced European options written on S&P 500. I found that the affine GARCH model (Heston-Nandi) with news impact consistently outperformed the pure affine GARCH model (Heston-Nandi). Nevertheless, the pure NGARCH and pure GJR model demonstrated smaller option pricing errors than their counterparts with certain macroeconomic news impacts. Therefore, I can conclude that scheduled macroeconomic announcements are sufficiently captured by classical non-affine GARCH models that do not explicitly use data on news arrivals. Additionally, non-affine GARCH models with and without news impacts always outperform affine GARCH models in terms of option valuation.

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